MULTI-DOMAIN MACHINE LEARNING FOR PREDICTIVE ELECTRIC VEHICLE CHARGING MANAGEMENT: A FRAMEWORK INTEGRATING BEHAVIORAL, INFRASTRUCTURE, AND MARKET DATA

by

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A dissertation submitted in partial fulfillment of the
requirements for the degree of

DOCTOR OF PHILOSOPHY IN
SYSTEMS ENGINEERING

2026

Oakland University
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This dissertation is dedicated to my husband, children, mother, and siblings for their unwavering support

ACKNOWLEDGMENT

First and foremost, I would like to express my deepest gratitude to Almighty God for granting me the strength, patience, wisdom, perseverance, and determination to complete this doctoral journey. His guidance and blessings sustained me through every challenge and gave me the faith and resilience needed to reach this important milestone.

I would like to extend my sincere appreciation to my dissertation chair and advisor, Dr. Mohamed A. Zohdy, for his guidance, mentorship, academic feedback, and support throughout this doctoral process. His expertise, recommendations, encouragement, and constructive feedback contributed significantly to the development and completion of this dissertation. I am especially grateful for his belief in my abilities and potential, which provided motivation and confidence throughout this academic journey.

I am also grateful to my dissertation committee members, Dr. William Edwards, Dr. Chris J. Kobus, and Dr. Erica Ruegg, for their valuable insights, recommendations, and thoughtful feedback. Their comments and suggestions helped strengthen the quality, clarity, and presentation of this research.

I would like to acknowledge Oakland University and the Department of Industrial and Systems Engineering for providing the academic environment, resources, and institutional support necessary for completing this doctoral work.

Special thanks are extended to my colleague, Dr. Muhammad Alolaiwy, the Office of the Registrar, the University Libraries, friends, and everyone who generously gave their time or contributed directly or indirectly to the completion of this journey. Each word of encouragement, thoughtful suggestion, and act of support was appreciated.

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ABSTRACT

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The growing popularity of electric vehicles (EVs) is bringing to light several new challenges that the infrastructure of the management of charging and smart grid operation as well as energy demand planning have to cope with. The accuracy of the prediction of the EV charging pattern can significantly increase the charging station utilization, reduce the risk of grid overload and enable the integration of renewable energy sources and also support development of future intelligent transportation systems. However, the majority of the EV charging prediction models being used nowadays are developed on the basis of a single domain dataset, and they are not able to capture or show the complex web of user-charging behavior, charging station features and market-related factors interaction. These limitations prevent such models from being applied in diverse scenarios and also from being deployed for actual charging purposes. With an aim to counter these issues, we present an innovative Multi-Domain Machine Learning Framework for EV Charging Prediction in this work. By combining datasets of different types, it enhances accuracy, robustness, and readiness for deployment of the predictive models.

The proposed framework integrates three publicly available datasets describing EV charging behavior, charging infrastructure, and dynamics of the EV market.

A preprocessing pipeline was developed to do data cleanup, filling missing data, removing duplicates, converting timestamps into the same time format, categorical encoding of variables, scaling of numeric features, and treatment of class imbalance. It should be noted that LightGBM was used to make an efficient computation and strong performance model on the data that is in structured tables, while TabNet made use of sequential attention mechanisms for carrying out interpretable deep learning on heterogeneous tabular datasets. Accuracy, Weighted F1-score, Macro F1-score, confusion matrix analysis, confidence calibration, computational efficiency, and ensemble weight optimization were used as evaluation metrics.

The results from the experiments show that the combination of different information types, including behavioral, infrastructure, temporal, and market-related, leads to a significant improvement in predicting performance compared to datasets when individual datasets are used. XLM-RoBERTa was the model that delivered the highest classification accuracy of 98.76% when tested against the integrated multi-domain dataset, while TabNet and LightGBM came in second and third at 96.89% and 85.67%, respectively. It is further revealed from the study that TabNet offers a good trade-off between predictiveness and computational requirements in a system. In contrast, LightGBM is not only the fastest but also requires minimal computing, which makes it a choice for systems under a tight budget. Through the ensemble weight optimization strategy, prediction reliability was enhanced since it assigned each model the best possible contribution. It is clear from this that transformer-based contextual learning can be successful, even under heterogeneous EV charging environments. These results contribute to the development of

ML technologies applied to the electric mobility sector and, most importantly, lay a groundwork for future intelligent EV charging solutions and smart city infrastructures.

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CHAPTER ONE

INTRODUCTION

1.1 Introduction and Background

Due to the rapid change of transportation systems through the widespread use of electric vehicles (EVs), it's becoming cleaner and faster for people to move from one place to another. The development and use of electric vehicles are speeding up the shift that is already happening toward a clean and sustainable form of mobility [1, 2]. This is mainly due to a few reasons: more worries about the environment, laws that require it, getting a bit better with batteries, and a global movement to change energy systems in sustainable ways. Moving from fossil fuels to other forms of energy is important because the use of fossil fuels causes climate change, which in turn causes environmental deterioration. It can be said that the use of fossil fuels is a major factor. People who rely on ICE cars emit pollutants such as greenhouse gases into the air, which in effect pollutes the air, and people continue to depend on fossil fuels; all of these contribute to climate change as well as environmental degradation [3]. As a result, the global powers, including both the government and the industrial world, have come forward to back up initiatives that promote electric vehicles as one of the strategies that can help meet the objectives of carbon neutrality and sustainable transportation. Besides, with the advent of electric vehicles that are much Cleaner, quieter, and less greedy in terms of energy, they are already regarded as one of the indispensable pillars of a smart city and intelligent transportation system of the future [4].

In the last 10 years, the global EV market has expanded significantly. According to the International Energy Agency, the global sales of electric cars hit 17 million vehicles in

2024, which has placed the segment among the fastest-growing sectors of the automobile industry [5]. To ease into the EV era, governments in Europe, North America, and Asia have been offering people various incentives. They've given out subsidies, let you avoid parts of your taxes, imposed regulations that help the environment, and launched public programs related to building necessary infrastructure. Moreover, China, the US, Germany, Norway, and the UK, among others, are putting a lot of effort into charging infrastructure and smart grid upgrades, which are two main factors in getting EVs to take off all over the place [6]. Along with changing the nature of transportation, the shift toward electric vehicles is also significantly affecting electricity distribution and transmission networks.

Electricity markets, energy policies of cities, and integration of renewables are just some areas besides energy generation that are undergoing changes due to this shift.

The issue that is new and associated with the rising proportion of EVs is the difficulty of power systems in coping with various large-scale challenges. One of the most pressing problems is the unpredictable and variable nature of EV charging demand [7]. While a home, office, or factory mainly uses energy only during working hours, or, to a lesser degree, for living in the evenings and weekends, EV charging can vary a lot and depends on the time of day, the habits of the owner, the places where the charging is done, and many other factors [8]. If we do not limit or control EV charging, it can lead to situations where the network is going to be heavily loaded and unstable, where transformers might get overloaded, there will be fluctuations in frequency, and there will also be high peaks in the demand for electricity. The biggest problems are when especially high numbers of EVs decide to connect to chargers at the same time during peak hours. Therefore, a precise EV charging forecast is now one of the most important tasks for intelligent energy management and smart-grid optimization, as shown in (Figure 1.1).

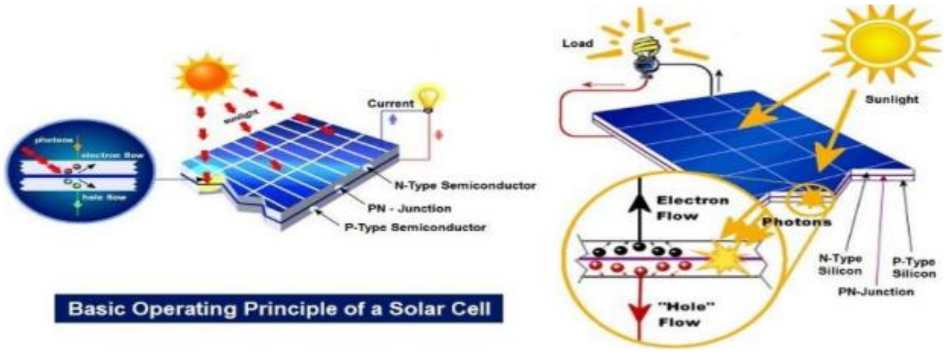


Figure 1.1: Basic operating principle of a photovoltaic (PV) solar cell illustrating photon absorption [9]

EV chargers' integration with smart-grid technology is a promising way to solve the abovementioned problems. Smart grids, a term for which there is no universally agreed-upon definition, share the common feature of extensive use of advanced sensing technologies, Internet of Things (IoT) devices, real-time monitoring systems, communication networks, and intelligent analytics to optimize electricity generation, distribution, and consumption [10]. With smart charging techniques, EV charging loads can be programmed, shifted, or run at their optimal level considering grid conditions, renewable energy availability, and user preferences [11]. Nevertheless, the performance of the charging systems implementing these intelligent features will be significantly influenced by the level of accuracy and reliability that the EV charging demand prediction models can provide.

AI, ML, and DL constitute a family of programming techniques allowing computers to learn from data and make decisions without being explicitly programmed. Their surge to lead the prediction of EV charging has been remarkable and fast. At first, techniques such as [12], Seasonal ARIMA (SARIMA) [13], and statistical regression models were used for short-term load forecasting [14]. Although their performance on linear and stationary datasets is pretty good, they have a hard time capturing the complex nonlinear relations, temporal dependencies, and heterogeneous contextual patterns of EV charging data [15, 16]. With more complex and diversified EV systems as well as the related data, it has become obvious that the regular forecasting techniques fall short in dealing with big charging datasets from various sources. Random forest, Support Vector Machines (SVMs), XGBoost, and LightGBM are examples of major machine learning algorithms.

These algorithms have been able to outdo the usual statistical models in the case of complex non-linear patterns and large data sets. Tree-based Ensemble learning has become especially popular in the field due mainly to its efficiency in calculation scalability as well as a very good level of predictions. Unfortunately, however, even these kinds of algorithms find it hard to describe long-term dependencies and changes in time that characterize, for example, EV charging.

With the availability of super-fast deep learning frameworks, we can finally dream of electric vehicle (EV) charging done in a smarter way. RNN, LSTM, GRU, CNN, and TCN have been used quite a bit in the domain of spatiotemporal forecasting. They can automatically extract complex features as well as temporal dynamics from the charging data. However, it has been widely accepted that sequence-based methods, such as LSTM and GRU, are characterized by a few serious disadvantages, such as difficulty for the model to remember long-term dependency, lower computational efficiency, and the problem of the deterioration of the gradients, particularly, when working with large-scale sequential data.

In brief, a transformer-based architecture has revolutionized the field of sequence modeling and forecasting with its capability in self-attention and capturing the whole context relations at the same time. Initially developed for NLP, nowadays they have also become an essential tool in domains such as vision, healthcare, finance, and especially energy and forecasting. The contextual learning methods like BERT and XLMRoBERTa have been reimagined as attention-based feature learning methods. In comparison to recurrent structures, transformers are different in the way that they accept the inputs and process them simultaneously and capture long-range dependencies easily, and thus they are suitable for analyzing EV charging patterns.

Besides transformer models, there have lately appeared other targeted deep neural network architectures for processing structured tabular data have lately appeared that are able to function as equally efficient substitute models for multi-modal data inputs. TabNet utilizes a repeated attention mechanism and performs feature selection of features on a per-sample basis, which helps in improving both the interpretability as well as the classification performance of mixed-type data. On the other hand, by means of its very fast gradient boosting optimization of structured infrastructure datasets, LightGBM provides an alternative with far reduced computational demands.

Although certain promising approaches for forecasting EV charging sessions have been proposed very recently by different groups of researchers, a major number of unresolved problems have still been left after the pioneering results, and these problems are many and very deep for example, majority of the studies is limited to single-type datasets such as either only behavioral charging sessions or only infrastructure information, completely neglecting the possibility of integrating different contexts. Moreover, a great percentage of studies run into data quality problems, data preprocessing issues, improper confidence calibration, class imbalance, and extremely limited assessment of deployment readiness level. Finally, the prevailing methods often fail to combine behavioral patterns, infrastructure metadata, and market dynamics into one integrated predictive framework that could be both scalable and realistically viable.

Hence, this study proposes a novel multi-domain machine learning system for the smart prediction of EV charging orders through the use of transformer-based and hybrid deep learning models. This system combines different datasets related to charging activities, infrastructure information, and market behavior to increase the predictive robustness of the model and its generalization ability. Three radically different deep learning model architectures, XLM-RoBERTa, LightGBM, and TabNet, will be examined both independently and together with cross-dataset experiments. The integration of such comprehensive processes as preprocessing of data, feature extraction, correlation mapping, confidence score computation, and readiness check for deployment will provide sufficient assurance of high-quality performance and effectiveness of the models in real-life scenarios. The significance of this work is not just in accurate forecasting. Indeed, predicting EV charging very accurately with the help of our framework can greatly assist in locating smart charging stations, smart grid planning & operation, managing energy load, Renewable energy utilization, demand-side management, dynamic pricing methods, and sustainable city development.

Also, our framework will help to realize the ongoing development of intelligent transportation systems and smart cities of the future by providing an efficient, adaptive, and data-driven EV charging infrastructure management system.

This work aims to bridge the gap between the latest advances in artificial intelligence and the practical needs of smart grid implementation through a strong, scalable, high-performance EV charging prediction model capable of addressing energy and transportation challenges today.

1.2 Problem Statement

The global electrification of vehicles has raised the need for an extensive, intelligent, and highly efficient charging network. As more and more people switch to electric vehicles, the providers and operators of charging stations, as well as the policymakers, are facing increasing challenges to manage the load of charging demand, maximize the use of facilities, minimize grid congestion, and ensure a steady energy supply. Therefore, a correct forecast of electric vehicle charging patterns is now a key aspect of EV charging control and smart transportation programs.

However, the biggest shortcoming of the latest machine learning for electric vehicle charging foresight research is the neglect of multiple factors. Most of the research is conducted on a single-type database, such as electric vehicle charging session data, charging point location data, electricity consumption statistics, etc., thus not considering the relationship between user behaviors on the one side and infrastructural, temporal and market-conditions on the other side.

[17]. Such models are, therefore, not suitable for capturing the various aspects of electric vehicle charging systems, so they produce low prediction accuracy levels and are not transferable to other environments. A large number of forecasting models employ just plain machine learning methods or a solitary deep learning network without doing a thorough comparison of the different learning methods [18]. The combination of these techniques and their use for multi-domain electric vehicle charging forecasting have been largely absent from previous literature and/or only locally addressed. As mentioned earlier, while most of the literature has concentrated on enhancing prediction accuracy, other vital aspects like model accuracy, system efficiency, confidence calibration, and deployment readiness have hardly been discussed, and yet, they play a really important role in developing practical intelligent charging systems.

Because of the issues highlighted earlier, the research proposes a Multi-Domain Machine Learning Framework for Electric Vehicle Charging Prediction that can fuse diverse datasets like charging behavior, temporal factors, charging infrastructure, and market dimensions into a single forecasting method. This brand new framework uses machine learning models like XLM-RoBERTa, LightGBM, and TabNet for pattern recognition and discovery over multiple data sources, leading to better forecasting. The main idea of the paper is to suggest, through extensive data processing, feature engineering, cross-domain data integration, and performance analysis, a robust prediction framework that would be suitable for smart grid optimization, intelligent infrastructure charging management, sustainable planning, and other uses.

1.3 Objectives of the Research

Developing a machine learning framework that is reliable and gives accurate results through a multi-domain approach for EV Charger-Type prediction is the main focus of this study. This multi-domain machine learning model aims to raise prediction accuracy, broaden the model's generalization, providing a management system of EV charging intelligent and ready-for-deployment solution.

The main aims of this study are listed below:

I. The objective is to analyze the effects of behavioral, temporal, infrastructure, and market features in predicting EV charger type.

II. This research shall create a multi-domain data integration scheme that merges different and heterogeneous EV charging datasets into a homogeneous feature representation for ML models.

III. This research is expected to formulate elaborate data cleaning, transformation, encoding, and integration algorithms for the multi-domain EV charging data after the data preprocessing and feature engineering phases.

IV. XLM-RoBERTa, LightGBM, and TabNet will be implemented as deep learning frameworks to predict EV charger type based on a given input data. Performance evaluation of these deep learning models will also be done too.

V. The predictive power of the models proposed will be evaluated via the use of multiple evaluation criteria including accuracy, precision, recall, weighted F1-score, and macro F1-score, etc.

VI. The efficiency of multi-domain data integration at enhancing the quality of predictions of the models will be checked against that of the predictions based on each data domain as a standalone.

VII. In this study, the possibility of using the proposed model on an integrated intelligent EV charging infrastructure management, smart grid, and sustainable transportation system will be discussed.

1.4 Research Questions and Hypotheses

This study is going to explore whether prediction of charger-type (i.e. whether the electric vehicle is charged at plug or socket) using machine learning approach and incorporating heterogeneously different data sources will result in better performance than the presently used methods for EV-charging forecasts.

The research questions and hypotheses listed below define the scope of the study.

Research Questions

i. What effect does the behavior-related factors like behavior, temporal-related factors and market-related factors among these categories have on predicting the type of EV charger which would be best for a given situation in terms of the location of the chargers or the types of EVs which are expected, etc?

EV charging behavior is influenced by a range of complex factors that interrelate to each other like user habits, the duration of the time, characteristics of the charging station, its location, and market trend, among other things. This question aims to examine whether these heterogeneous features can improve the understanding and prediction of charger-type usage.

ii. Does the amalgamation of EV charging datasets from multiple domains enhance the model's prediction capability in comparison with models trained on single-domain datasets?

Many of the prior works have focused on just one data source, like charging sessions, station locations, or energy consumption records. This research question is about checking if the integration of behavioral, temporal, infrastructure, and market-related data into a combined framework can contribute to a prediction system that is not only more accurate, but also resilient and general.

iii. What machine learning model gives the highest performance reliability for EV charger type prediction?

Models like XLM-RoBERTa, LightGBM, & TabNet have different strengths and limitations such as accuracy, interpretability, and computational speed. This section will compare these models in detail to find the optimal strategy for smart EV charging prediction.

iv. Can the proposed multi-domain machine learning framework support scalable and deployment-ready EV charging infrastructure management?

Accurate charger-type prediction can support charging station planning, smart-grid integration, demand management, and sustainable transportation systems. This question evaluates whether the proposed framework is practical, efficient, and reliable enough for real-world EV charging applications.

Research Hypotheses

H1: Integrating behavioral, temporal, infrastructure, and market-related datasets does not significantly improve EV charger-type prediction performance compared with single-domain datasets.

Justification: Integrating behavioral, temporal, infrastructure, and market-related datasets significantly improves EV charger-type prediction performance compared with single-domain datasets.

H2: There is no statistically significant difference in predictive performance among XLM-RoBERTa, LightGBM, and TabNet for EV charger-type prediction.

Justification: There is a statistically significant difference in predictive performance among XLM-RoBERTa, LightGBM, and TabNet, with at least one model achieving superior prediction accuracy and reliability.

H3: The proposed multi-domain feature engineering and data fusion framework does not significantly enhance model robustness, confidence calibration, or deployment readiness.

Justification: The proposed multi-domain feature engineering and data fusion framework significantly enhances model robustness, confidence calibration, and deployment readiness for intelligent EV charging systems.

The above research questions and hypotheses provide the foundation for the proposed methodology and experimental evaluation presented in the subsequent chapters.

1.5 Scope and Limitations

Scope

The goal of our research was to design, implement, and evaluate a machine learning system that can predict different EV charger types across domains smartly. This research gathered varied datasets representing the facets of EV charging such as how the users operate, the number of charging spots, and the features related to time, and the business data. The combination was performed in such a way not only to make predictions more accurate but also to enhance the generalization of the models which refers to how well a model performs on new and unseen data.

Several public EV charger datasets have been merged in this study after being preprocessed to show different sources of data through data preprocessing, feature engineering, multi-domain data blending as part of the efforts to produce one consolidated dataset.

Our proposed method consists of a number of steps including but not limited to, data cleaning, the handling of missing values, categorical encoding, feature normalization, and the use of temporal (time-related) features as well as combining features to build an enriched feature space that the machine learning models will rely on.

Three state-of-the-art machine learning models were implemented and tested in order to identify the most suitable model for predicting EV charger type prediction, besides Accuracy, Precision, Recall, Weighted, Macro, ROC-AUC, model evaluation also covers a confusion matrix, a confidence map, and runtime analysis for model execution. Also, the paper discusses ensemble weight adjustment in terms of checking if a combined model can potentially out-perform.

Besides accurate charging predictor, the framework also has a role in smart charging through the prediction and identification of different charger types so that a wide array like the use of charging facilities, power consumption, energy management, and other support decision systems can be better planned. Along with prediction accuracy, this research will also touch on model deployment speed, one of the factors affecting the usefulness or applicability of predictive models.

Limitations

Several weaknesses must be recognized even though our framework is highly accurate in prediction and has excellent generalization ability.

First, we used only publicly available datasets which might not cover charging behavior in every geographical area, climate, transportation system, and EV user population.

Hence, to a large extent, the developed models' generalizability would be further enhanced if validated with region-specific operational datasets.

This research narrowly focuses on three machine learning models namely XLM-RoBERTa, LightGBM, and TabNet. Whereas other state-of-the-art architectures such as Graph Neural Networks (GNNs), Temporal Graph Networks (TGNs), Vision Transformers, Temporal Fusion Transformers (TFTs), and Large Language Model (LLM)-based prediction frameworks have not been explored and were out of scope.

Also, experiments done in this study were limited to offline learning scenarios with historical datasets. Issues like real-time deployment, continuous online learning, streaming data processing, and adaptive model updating have been left out. As a result, the question of the framework's adaptability to constantly changing charging environments remains open.

The proposed ensemble learning scheme did result in improved prediction stability; however, the ensemble weights were tuned using offline experimental analysis. Real-time or adaptive ensemble learning methods that can automatically adjust model weights based on real-time charging conditions have not been considered.

The computational expense of XLM-RoBERTa is still quite high compared to LightGBM and TabNet. Even though the transformer model yields the best prediction results, further thoughts such as model compression, pruning, quantization, and knowledge distillation may be necessary before its use on edge devices and resource-limited charging stations.

1.6 Structure of the Dissertation

In terms of layout, this dissertation consists of 8 chapters. Each chapter centers around one step of the research cycle such as problem statement, solution design, and solution evaluation along with discussion of results and drawing a scientific conclusion of the multi-domain machine learning framework proposed for electric vehicle (EV) charger-type prediction. As it progresses, the dissertation presents a coherent transition from the theoretical basis to the practical execution of the framework and finally to its assessment.

Chapter One: Introduction

The introduction of the dissertation outlines the background of the research area, the problem being addressed, the aims of the research, the research questions and hypotheses, the scope and limitations, the relevance of the study, and the dissertation structure in general.

Chapter Two: Background

Background gives you an overview of fundamental topics like electric vehicles, green transportation, EV charging facilities, charging habits, predicting charging requirements, use of algorithms for machine learning, artificial neural networks for deep learning, and much more. It helps in understanding the research proposal, presenting the necessary fundamentals and concepts here.

Chapter Three: Literature Review

A Literature Review involves an appraisal of the works already done on predicting EV charging by using statistical methods, machine learning algorithms, and deep learning techniques. It discusses the findings of these works, draws out their dominant aspects and weak points, points out research gaps, and creates a rationale for the development of a unified multi-domain prediction framework. The chapter ends by giving the grounds for the proposed research methodology.

Chapter Four: Research Methodology

Research Methodology introduces the general research design and methodologies taken in this study. It describes the data gathering techniques, data cleaning methods, feature extraction and selection, multi-domain data resourcing scheme, model implementation of XLM-RoBERTa, LightGBM, and TabNet, model training mechanism, evaluation metrics, and the overall scheme of the experiment that was done for the assessment of the proposed framework.

Chapter Five: Mathematical Modelling

Mathematical Modeling gives a detailed mathematical representation of the proposed multi-domain machine learning framework. The major topics of this chapter are the mathematical description of the integrated dataset, guided feature extraction process, transformer-based XLM-RoBERTa model, LightGBM algorithm, TabNet architecture, ensemble learning strategy, optimization procedures, and evaluation metrics.

Chapter Six: Results and Analysis

Results and Analysis deals with the experiment results of the evaluation of XLM-RoBERTa, LightGBM, and TabNet that use individual datasets as well as the integrated multi-domain dataset proposed. The chapter carries out comparative performance analysis, confusion matrix evaluation, ROC curve analysis, confidence calibration assessment, computational efficiency analysis, ensemble weight optimization, and a comparison of the proposed models using multiple evaluation metrics.

Chapter Seven: Discussion on Results

Discussion on Results explains the experimental outcomes depicted in Chapter 6 and connects them with the research objectives as well as the existing literature. The chapter covers the success of the proposed multi-domain learning framework, evaluates the comparative performances of the reviewed models, discusses the tangible effects of the research, contrasts the results with previous studies, mentions the study limitations, and proposes the plan for future research.

Chapter Eight: Conclusion and Future Work

Conclusion and Future Work presents a brief overview of the most significant results and contributions of the research, assesses how well the research objectives were met, features the shortcomings of the proposed framework, and outlines suggestions for future research.

CHAPTER TWO

BACKGROUND

2.1 Chapter Overview

This chapter covers the theoretical and technical issues that are necessary to grasp an electric vehicle charging prediction. The chapter discusses electric vehicles, charging infrastructure, charging behavior, smart-grid integration, machine learning, deep learning, transformer models, tabular learning, multi-domain fusion, model reliability, and deployment readiness. The chapter aims to establish the basis for the suggested multi-domain machine learning framework, which combines behavioral, infrastructure, and market-level datasets for EV charging prediction.

2.1.1 Electric Vehicles and Sustainable Transportation

Electric vehicles are one of the main elements of sustainable transportation as they lessen direct emissions from cars, reduce reliance on fossil fuels, and promote low-carbon ways of getting around [19]. In contrast to vehicles with internal combustion engines, EVs are either entirely or partly driven by electricity stored in batteries that can be recharged [20]. Their use furthers the worldwide efforts to reduce the carbon footprint, particularly when the source of electricity for charging is renewable. Sustainable transportation means not only more environmentally friendly vehicles but also smart charging systems. When EV charging is done without any control, it might cause electricity distribution networks to be pushed to their limits. So, it is necessary to consider EVs and charging stations, user behavior, smart electrical grids, and forecasting methods as one system as shown in Figure 2.1.

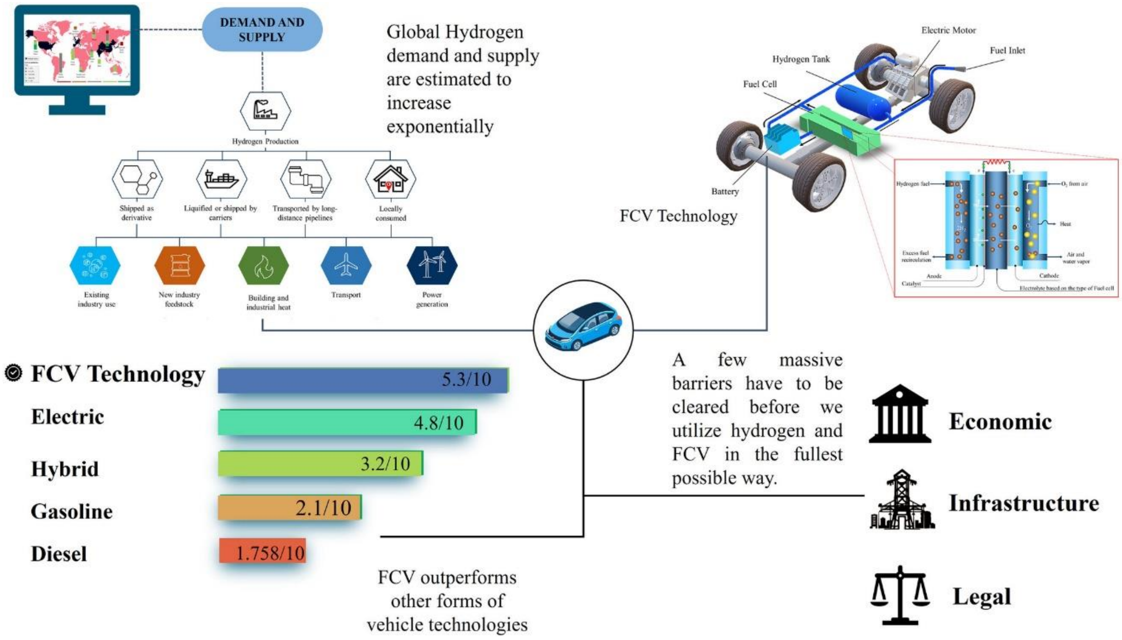


Figure 2.1 : Conceptual overview of hydrogen fuel cell vehicle (FCV) technology [21]

2.1.2 Global Growth of Electric Vehicle Adoption

The global market for electric vehicles (EV) has grown really fast lately. For instance, based on the information provided by the International Energy Agency, the number of global electric vehicle sales was more than 17 million in 2024, and it is estimated that at least 20% of the vehicles sold globally are electric ones. Besides that, [22] shows that the numbers of electric vehicles, batteries, charging infrastructure, and the policy support of major markets are increasing at an impressive rate.

Then, the [23] EV data explorer has more comprehensive data on the sales, stock, charging infrastructure, and oil-displacement of electric vehicles with projections as shown in Table 2.1.

Table 2.1 Global EV Adoption Evidence Future

Reference	Key Evidence
IEA Global EV Outlook [24]	EV sales exceeded 17 million in 2024
[25]	Tracks EV sales, stock, charging infrastructure, and projections
[26]	Reviewed ML-based EV charging demand forecasting trends
[27]	Proposed data-driven EV charging demand forecasting using station data

2.1.3 Electric Vehicle Charging Infrastructure

Electric vehicle charging infrastructure is made up of both the tangible and intangible elements that help deliver power to electric cars [28]. The main components of a charging infrastructure are charging points, cables, electrical converters, payment methods, communication units, tracking systems, and grid-management interfaces [29]. The charging infrastructure could be located at residential areas, offices, public parking spaces, expressways, shopping malls, and fleet storage sites. Location-dependent charging requirements combined with time, vehicle types, user habits, charger availability, and the capacity of the grid mean that infrastructure planning has become the major concern. Badly planned infrastructure can lead to the overcrowding of charging points, customers having to wait for a long time, chargers being left idle, and local power grid issues.

2.1.4 Types and Levels of EV Chargers

EV chargers are most often divided into groups by charging speed and power level. Level 1 chargers are the minimum speed and mostly home chargers. Level 2 chargers are also faster and quite home and workplace and public location. DC fast chargers provide high-power charging and are used for highways, commercial hubs, and rapid charging stations as shown in Table 2.2.

Table 2.2 EV Charger Types and Characteristics

Charger Type	Typical Use	Charging Speed	Infrastructure Requirement	Prediction Importance
Level 1 AC	Home charging	Slow	Low	Useful for long-duration residential behavior
Level 2 AC	Home, workplace, public parking	Medium	Moderate	Important for daily charging behavior prediction
DC Fast Charger	Highways, commercial stations	Fast	High grid capacity	Critical for demand peaks and infrastructure planning
Ultra-fast Charger	Highway corridors, fleet hubs	Very fast	Very high grid support	Important for grid stability and future charging networks

2.1.5 EV Charging Sessions and Charging Behavior

EV charging session means the entire cycle of charging from the time when the EV is plugged into the charger until it is unplugged [30]. It encompasses start and end times, duration, energy consumed, type of charger, charging location, and on some occasions user or vehicle information.

As charging behavior is subject to changes in human routines, travel patterns, battery state of charge, electricity price, and charger availability, it is also affected by the purpose of the trip.

From a machine learning standpoint, charging sessions are valuable as they reveal temporal and behavioral patterns. For instance, a user might charge the EV mainly during nighttime, at work, or right before a long drive. One can convert such patterns into well-defined features like hour of day, day of week, charging duration, energy consumed, and charging frequency.

2.1.6 Factors Affecting EV Charging Demand

The demand for electric vehicle (EV) charging is influenced by various diverse factors: technical, behavioral, spatial, economic, and environmental ones [31]. Technical factors consist of elements such as battery capacity, charger power, connector type, and charging efficiency [32]. Behavioral factors encompass aspects like arrival time, departure time, travel routine, and user preference [32]. Spatial factors include station locations, urban density, traffic flow, and proximity to workplaces or highways. Economic factors, on the other hand, comprise electricity price, charging tariff, fuel price, and incentive policies as shown in Table 2.3.

Table 2.3 Main Factors Affecting EV Charging Demand

Factor Category	Examples	Impact on Charging Prediction
Temporal	Hour, weekday, season, holiday	Determines peak and off-peak charging
Behavioral	User routine, trip purpose, charging preference	Explains irregular charging patterns
Infrastructure	Charger type, station capacity, connector availability	Determines service capacity and waiting risk
Spatial	City, road network, station location	Supports regional demand forecasting
Economic	Electricity price, tariff, incentives	Influences charging time and station choice
Energy System	Grid load, renewable availability	Important for smart charging and load management

2.1.7 Challenges in EV Charging Infrastructure Planning

Charging infrastructure planning encounters quite a few problems. For example, in a lot of areas, the number of electric vehicles is growing much faster than the number of places to charge them [33]. Besides, the need for charging stations varies quite a bit from one place to another and even at different times of the day [34]. Also, since people's traveling and charging habits vary, their charging behavior is quite unpredictable. Another point is that data at the station level may be plagued with missing values, inconsistent labeling, duplicated records, and insufficient metadata. Finally, one cannot just turn a blind eye to grid limitations when dealing with the installation of high-power chargers. Literature is increasingly acknowledging the importance of accurately predicting electric vehicle charging to the extent that such forecasting is essential for the efficient planning of the infrastructure, the use of renewable energy, and the power grid stability. Although machine learning has been employed to the forecasting of demand, the designing of stations, and the behavior patterns analysis at charging stations, reviews covering the area in detail have shown an upward trend of the use of the prediction models.

2.1.8 Smart Grid Integration and EV Load Management

Smarter electricity systems involve the integration of technologies such as sensors, communication networks, real-time monitoring and intelligent control systems for handling electricity generation, distribution, and consumption [35]. Different methods of incorporating EVs into smart grids are smart charging, demand response, vehicle-to-grid systems, and varying prices depending on supply and demand [36].

Smart charging is an approach that allows the charging of electric vehicles to be switched or optimized according to the grid conditions. For example, charging can be moved to different periods of the day when the demand on the grid is low instead of doing it in peak hours. This has the dual advantage of reducing the risk of transformer overload in addition to supporting a stable voltage and promoting renewable energy use. The accurate prediction of future EV charging demand including when, where and how much should be done plays a key role in the functioning of smart grids. Therefore, it can be said that predictive analytics acts as the nerve center of such grids.

2.1.9 Role of Predictive Analytics in EV Charging Systems

Predictive analytics use of past and current data to figure out the future demand for charging stations, how chargers would be used, amount of energy to be consumed, number of people gathered at a site, and loading patterns [37]. It enables the operators to strategize the installation of chargers, handle peak loads, minimize waiting time, and enhance the experience of users. EV charging forecast can be of various kinds such as demand forecasting, predicting session duration, forecasting energy consumption, occupancy prediction of a station, and prediction of the type of charger [38].

2.1.10 Machine Learning in EV Charging Prediction

Machine learning models are capable of discovering nonlinear relationships in EV charging datasets. Among these models are Random Forest, Support Vector Machine, XGBoost, LightGBM, CatBoost, and regression-type models. They work well with tabular datasets, particularly when the features are charging duration, power level, location, station capacity, and energy consumption as shown in Table 2.4. According to the most up-to-date reviews, ML-powered EV charging forecasting is now a hot research area since traditional statistical models cannot usually handle complex and nonlinear charging behaviors adequately [26].

Table 2.4 Machine Learning Models Used in EV Charging Prediction

Model	Strength	Limitation	EV Charging Application
Random Forest [39]	Handles nonlinear data	Less interpretable than single trees	Demand and behavior prediction
XGBoost [40]	High accuracy on structured data	Requires tuning	Load and session prediction
LightGBM [41]	Fast and scalable	Sensitive to data imbalance	Infrastructure and tabular prediction
SVM [42]	Effective for smaller datasets	Computationally expensive for large data	Classification tasks
Logistic Regression [40]	Simple and interpretable	Limited nonlinear modeling	Baseline prediction model

2.1.11 Deep Learning Models for Charging Demand Forecasting

Deep learning models are very popular for EV charging forecasting as they are capable of capturing complex changes over time and space. LSTM, GRU, CNN, TCN, as well as mixtures of these, are applied in forecasting EV charging demand for very short time through to long time. For instance, Van Kriekinge et al. came up with deep neural network for day-ahead EV charging demand forecasting in 2021 [43]. [44] implemented deep spatio-temporal forecasting for EV charging demand based on publicly available data. While recent research is also mixing transformer and LSTM encoder-decoder structures for EV charging station demand forecasting.

2.1.12 Transformer-Based Models for Sequential Charging Behavior

Transformer models are mainly known for their self-attention mechanisms, which help them capture dependencies even if they are very far apart in the text. In predicting EV charging, we can think of a charging event as a sequence that includes time, duration, energy, location, and charger information. Transformers are known to be better at learning connections between such events compared to the old recurrent models [45].

CHAPTER THREE

LITERATURE REVIEW

3.1 Chapter Overview

With the electrification of the vehicle fleet progressing rapidly, intelligent prediction of charging demand has become a hot topic as it makes the accurate projection of future demand for charging services and ensures the stable operation of power grids, effective utilization of charging infrastructures, and satisfaction of users possible. Charging demand for electric vehicles is affected by various factors that interact with each other like the pattern of charging, features of the charger, weather, traffic conditions, prices of electricity, availability of renewable energy, and local extent of EV adoption.

Rather different are the researchers' motivations for developing such complex relationships into various machine learning statistical or deep learning methods. Deep learning models have become the latest fashion, and they have demonstrated great success in uncovering the nonlinear time dependencies in charge cycles and the sequential patterns in charge behaviors with models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), Temporal Convolutional Networks (TCN), and Transformer-based models.

While many scientists have already looked into the issue, the research still varies a lot. Most of the time, a paper is based on only one kind of data, the paper discusses a single aspect of EV charging (i.e., charging demand or energy consumption), and the simultaneous use of different data kinds, such as charging logs containing behavioral information, features of charging stations, and market-level data into one predictive model is rare.

Also, very few papers are trying to evaluate their models in terms of trustworthiness, confidence calibration, effectiveness over different data domains, and readiness for deployment in charging systems at the real-world level. This research were inspired to bridge these gaps mainly by developing a broad machine learning approach that spans multiple data sources. It not only will be capable of harnessing the advantages offered by each of the distinct data types but will also be highly accurate and useful at the same time.

3.2 Electric Vehicle Charging Prediction: Research Context

EV charging demand prediction has become one of the most popular research topics in intelligent transportation systems because it directly affects the distribution of electricity, charging station use, integration with renewable energy and smart-grid management. With the global proliferation of EVs over time, charging demand has become more and more unpredictable because of user's behaviors, charging preferences, charging infrastructure, travel patterns, electricity prices, and environmental conditions. Hence, risk models are now being regarded as very crucial tools for alleviating charging congestion, improving energy management efficiency, and even assisting the infrastructure planning over time [26]. In the beginning, studies on predicting EV charging focused mostly on calculating the total electricity demand based on past charging data and statistical methods of forecasting. Current prediction models usually combine time, location, behavior, environment, and infrastructure data to achieve higher levels of forecasting accuracy for various prediction times ranging from short-term to medium-term to long-term [46].

Roozkhosh et al. [17] examined the spatial forecasting of the charging station demand by combining geographical information, the features of the charging stations, and the regional data of the EV registrations. Their research showed that spatial factors significantly enhanced the accuracy of the demand forecast than the models based only on the temporal variables. Nevertheless, the proposed model put the main focus on the information related to the infrastructure and was missing the detailed behavioral patterns of the charging sequences, which constrained its ability to depict user-specific charging behaviors.

Alaraj et al. [26] conducted an extremely thorough systematic literature review on the topic of machine learning based forecasting of EV charging demand. Their work classifies forecasting models in terms of prediction horizon, type of machine learning algorithm and domain application. At the same time, they pointed out the main developments in xAI, hybridization of forecasting techniques and transformer-based models. They opined that further research should focus on multi-modal data fusion, unified benchmarking frameworks, and production-ready machine learning solutions.

Tolun et al.[18] did an extensive review and test of forecasting models based on statistics, machine learning, and deep learning for monthly EV charging demand prediction. The paper took into account SARIMAX, CNN, LSTM, Bi-LSTM, GRU, Bi-GRU, and XGBoost algorithms based on actual charging datasets available from Türkiye. Experimental findings verify that the machine learning and deep learning models are continuously beating the traditional statistical methods, especially when the non-linear charging patterns are getting more marked.

Hussain et al. [47] presented a charging station demand forecasting method based on LSTM encoder-decoder with Transformer attention by utilizing the ACN publicly available charging dataset. Their combined hybrid model was very effective in extracting long-term temporal dependencies and, at the same time, it resulted in a better forecast accuracy level than each of the LSTM and Transformer models separately. The proposed method, though very good for time-series forecasting, zeroed in on the charging demand only and, at the same time, it left out the use of the infrastructure metadata or market-level contextual information as shown in Table 3.1.

Table 3.1 Recent studies on EV charging prediction

Authors	Dataset	Method	Strength	Limitation
Roozkhosh et al.[17]	Station + GIS	Spatial ML	Strong geographic prediction	Limited behavioral modeling
Alaraj et al.[26]	Literature review	Systematic review	Comprehensive survey of ML methods	No experimental framework
Tolun et al.[18]	Monthly charging demand	SARIMAX, CNN, LSTM, GRU, XGBoost	Comprehensive benchmark	Single prediction objective
Hussain et al.[47]	ACN charging dataset	LSTM + Transformer	Excellent long-term forecasting	No multi-domain fusion

3.3 Traditional Statistical Methods for EV Charging Forecasting

Traditional statistical methods serve as the baseline for electric vehicle (EV) charging forecasts. Generally, these methods consider the charging load, charging sessions, or EV adoption as time-series data and forecast the future values based on the historical trends, seasonality, and occasionally external variables. Typical statistical models are ARIMA, SARIMA, SARIMAX, ARIMAX, persistence models, and regression-based forecasting. Even though statistical methods are usually less powerful than the state-of-the-art machine learning and deep learning models, they still are very valuable for being interpretable, computationally simple, and for benchmarking the advanced forecasting frameworks.

Kim et al. (2021) [39] investigated the forecasting of EV charging demand using multi-scale regional datasets collected over two years. The research compared various forecasting models in estimating the rise in electricity consumption due to EV charging. The dataset contained geographical and regional charging-related information. The authors noted that various factors such as vehicle condition, battery state of charge, travel distance, and regional usage patterns, influence charging demand. Their research indicated that no single model can be successful in all regions, hence statistical and baseline models are helpful but have limitations when charging behavior varies geographically. This research is essential as it shows the requirements for region-sensitive forecasting models in EV charging demand prediction.

Saraç et al., (2025) [48] used a SARIMA time-series model for their forecasting of the number of electric and hybrid vehicles in Turkey. The dataset they used was historical electric and hybrid passenger vehicle counts. The SARIMA model was chosen upon the basis that it can capture seasonal patterns and long-term trends in EV adoption. The findings indicate that SARIMA could be very beneficial in forecasting and national EV market Planning. They concentrated on EV adoption, not station-level charging load directly, yet still have logic behind it as EV proliferation directly determines the future charging infrastructure needs.

Çetin (2024) [49] applied SARIMA model in forecasting sales of electric vehicles The dataset he used for the study consisted of past EV sales figures and the prediction model served as an indicator of how the market would unfold. The paper states that the accuracy of the forecast has repeatedly been a strong point of SARIMA hence it becomes a strategic means of the preparation and deployment of resources that can help to satisfy EV market stakeholders through efficient utilization of resources. Besides, the drawback of the model, i.e. to overlook the aspects such as the patterns of charging-sessions, charger types, user habits or any of the charging requirements at the station level is a serious modelling gap. Conclusively, this gap indicates that although statistical forecasting can offer a broad strategic planning tool, it falls short when one wishes to anticipate fine details of EV charging behavior.

Roozkhosh et al. (2024) [17] If you look at the EV registrations over time, the types of connector used for charging and the geographical locations of charging stations one can forecast the demand for EV charging. To make their forecasting quite accurate, they combined time-series forecasting techniques with machine learning approaches. Apart from the growth in EV registrations, their dataset also reflected the charging connector types and geographical attributes of the stations. They found that, when both temporal and spatial datasets are considered, prediction accuracy enhances significantly. But time-series modeling alone was not sufficient to fully capture the EV charge demand dynamics because, for a particular charging station, the demand fluctuates not only in time but also, in part, with the locality, the level of development and also user habits.

Ostermann et al. [50] Investigated electric vehicle (EV) charging demand forecasting by employing probability, concentrating on forecasting for the next day and real-time periods. The forecasting was performed four different forecasting horizons: Day-ahead hourly forecast, Intra-day 1-hour-ahead forecast, Intra-day 15-min-ahead forecast. The dataset had different temporal resolutions of EV charging demand observations. Among its results, the study showed that short-horizon intraday forecasting can help operational decision-making; however, day-ahead forecasting is needed for electricity market participation and grid planning. This paper is very relevant as it takes the traditional deterministic forecasting one step further by mapping the uncertainty of forecasts shown in Table 3.2.

Table 3.2 Traditional Statistical Forecasting Studies in EV Context

Study	**Dataset**	**Model Used**	**Reported Results**	**Review / Limitation**
Kim et al. (2021) [39]	Multi-scale geographical EV charging-related datasets over two years	Statistical and forecasting models	Model performance varied across regions	Useful for regional demand forecasting, but limited for heterogeneous user-level behavior

Table 3.2 continued

Study	Dataset	Model Used	Reported Results	Review / Limitation
Saraç et al. (2025)[48]	Historical electric and hybrid passenger vehicle counts in Turkey	SARIMA	Produced national EV growth forecasts	Relevant for infrastructure planning, but not station-level charging prediction
Çetin (2024) [49]	Historical EV sales data	SARIMA	SARIMA provided reliable EV sales forecasts	Supports market planning, but lacks charging-session and infrastructure details
Roozkhosh et al. (2024) [17]	EV registration, connector type, and charging station location data	Time-series forecasting and ML models	Temporal-spatial features improved demand prediction	Traditional forecasting alone cannot fully model infrastructure and user behavior
Ostermann et al. (2024)[50]	EV charging demand data for day-ahead and intraday horizons	Probabilistic time-series forecasting	Evaluated day-ahead, 1-hour, and 15-minute horizons	Strong for uncertainty modelling

The studies reviewed here establish that statistical forecasting methods still have their place when it comes to EV-related forecasting, particularly if the goal is to capture historical trends, seasonality and aggregate demand. For example, SARIMA's strength is in dealing with situations where the data exhibit repeating seasonal patterns, e.g. monthly EV sales or regional EV adoption trends. Besides that, these ARIMA-type models are useful as clear baseline models because their framework is straightforward and they do not require much computational resources. On the other hand, the biggest drawback of classical statistical models is that at the core they lead to linearity, stationarity and historical temporal patterns. The demand for EV charging is dependent on several nonlinear and varied factors, e.g. user behavior, charging location, charger type, electricity price, connector availability, travel patterns, as well as regional EV adoption.

3.3 Machine Learning Approaches for EV Charging Demand Prediction

The increasing complexity of electric vehicle (EV) charging systems has prompted researchers to explore machine learning (ML) methods as an alternative to the purely statistical forecasting. Statistical forecasting methods only look at the historical timeline. But ML techniques allow uncovering a variety of complex nonlinear patterns in different parameters at once. These can include charging time, electrical consumption, type of charger, characteristics of the charging station, weather conditions, electricity rates, user mobility patterns, local EV adoption. Therefore, machine learning is one of the primary means of predicting the EV charging demand as it is capable of dealing with different datasets while providing simultaneously better prediction results.

A wide number of supervised learning techniques has been used to predict EV charging such as Decision Trees (DT), Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), CatBoost, Artificial Neural Networks (ANN), and ensemble learning methods. This has dramatically improved prediction accuracy beyond the conventional statistical technologies, especially with datasets that have nonlinear relationships between different time variables, behavioral factors, and infrastructure factors.

Zhang et al. [40] devised an explainable machine learning system to predict EV charging demand in smart grids with integrated renewable energy sources. The project drew on a publicly accessible California EV charging dataset that contained information about EV charging demand, renewable energy penetration, grid data, weather conditions, and features associated with charging stations. The authors put forward five machine learning techniques: XGBoost, LightGBM, CatBoost, Random Forest, and Linear Regression. It was found that XGBoost had the best accuracy of the set, and LightGBM was a far cry from being just the next fast training technique.

Besides that, to explain feature importance, SHAP (Shapley Additive Explanations) was applied in the paper, and two factors (renewable energy penetration and the occupancy level of charging stations) were found to be the main variables explaining the charging demand. Even though the new framework significantly increased the accuracy of the predictions, the paper relied only on structured tabular data without considering the sequencing of user charging behavior as well.

Che [51] created a Random Forest-based model for forecasting charging load by using the records of charging sessions collected from public EV charging stations. The dataset comprised the following session features: charging start time, charging duration, charging energy, battery state, and charger type. Among the considered models, the decision tree-based random forest algorithm was finally chosen as it is highly resistant to noisy data and can also describe the interactions between nonlinear features. The findings of the experiments showed that Random Forest has caused a significant increase in prediction accuracy compared to the conventional regression models while also displaying consistent performance across different charging situations.

Wang et al. [52] the authors compared various machine learning algorithms to determine which would be the most appropriate one for forecasting the EV charging demand based on public, open-source EV charging station datasets. Among the machine learning models examined were Random Forest, XGBoost, LightGBM, Decision Tree, Support Vector Regression (SVR), and Artificial Neural Networks.

The data sample included charging time, energy usage, weather, calendar, and charging station usage logs. Experimental results showed that LightGBM outperformed XGBoost both in RMSE and MAE scores while also providing a much faster computational time. The choice of the methods finally adopted can be hugely influenced by their good scalability and computational efficiency; thus, the authors have pointed out gradient boosting algorithms as very suitable for large-scale EV charging datasets.

Alaraj et al. [26] performed a thorough systematic review that dealt with more than 150 studies on the topic of machine learning methods for EV charging demand forecasting. The study categorized the forecasting methods into Decision Trees, Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost, Support Vector Machines, Artificial Neural Networks, and ensemble learning techniques and market-level information in one predictive framework, as shown in Table 3.3.

Table 3.3 Recent Machine Learning Studies for EV Charging Demand Prediction

Authors	Year	Dataset	Machine Learning Model	Results	Limitations
Zhang et al.[40]	2025	California public EV charging dataset	XGBoost, LightGBM, CatBoost, RF, Linear Regression	No behavioral charging sequence modeling	Zhang et al.[40]
Che[51]	2024	Public charging-session dataset	Random Forest	RF significantly outperformed traditional regression models	Unable to learn long-term temporal dependencies
Wang et al. [52]	2025	Public EV charging station dataset with weather and calendar variables	RF, XGBoost, LightGBM, Decision Tree, SVR	LightGBM achieved the lowest RMSE and MAE with faster computation	Limited to structured tabular features
Alaraj et al. [26]	2025	Systematic review of more than 150 EV charging forecasting studies	Comparative review of ML algorithms	XGBoost and LightGBM identified as the most effective ML methods	Most existing studies use single-domain datasets

3.4 Deep Learning Models for EV Charging Forecasting

Deep learning has emerged as a vital tool for forecasting electric vehicle (EV) charging demand since charging patterns of EVs are nonlinear, their demand changes over time, and they are affected by numerous external factors. Different from conventional statistical techniques, deep learning approaches have the ability to discover intricate data structures hidden in large-scale charging datasets without human intervention. Besides, they are capable of tracking very long-term time dependencies in demand, differentiating between complicated user behaviors, identifying trends in the usage of charging stations, and working out the nonlinear associations between the demand for charging and various external factors such as weather, time, traffic, and developments in the regional charging infrastructure.

Koohfar et al. [45] presented a framework for forecasting EV charging demand based on deep learning and realized through time-series charging load data. This work tested ARIMA, SARIMA, RNN, LSTM, and Transformer methods in predicting EV charging load demand. Their dataset contained EV charging load recordings that were used to evaluate different forecasting periods involving 7-day, 30-day, and 90-day prediction intervals. Transformer-based models delivered superior predictions results when compared to forecast performances of traditional statistical models and recurrent neural networks. The main contribution of this article lies in revealing that attention-based deep learning can model long-range dependencies in EV charging load much better than ARIMA and SARIMA. Nonetheless, the paper's chief concern was temporal charging-load data and did not bring charging infrastructure or market-level data into consideration.

Hussain et al. [47] created a new hybrid LSTM-based Transformer network for predicting the demand for EV charging stations. They utilized the open ACN datasets from Caltech and JPL charging stations. An LSTM encoder-decoder structure along with

Transformer attention was merged in the model to facilitate medium-term and long-term prediction. The model was put to the test for 30-day, 120-day, and 240-day forecasting horizons. For the Caltech dataset, the hybrid LSTM-Transformer managed to reduce MAE by up to 17.27% and MSE by 19.79% at the 30-day horizon, while for the JPL dataset, it was able to lower MAE by up to 24.91% and MSE by 23.17% at the 30-day horizon compared with baseline models.

Cavus et al. [53] have just launched HCB-Net, an advanced deep learning system that is quite novel and uses a mixture of approaches to forecast the demand for electric vehicles in smart cities. For their study, they employed behavioral and spatial data for two regions of England, namely the North East and the West Midlands. One component of the chain was a CNN to capture the spatial patterns, while XGBoost regression was used to get behaviors from the combination of patterns. HCB-Net was tested against Random Forest, XGBoost, SVM, LSTM, and CNN models.

The findings indicated that the hybrid CNN-XGBoost model outperformed conventional machine learning and standalone deep learning models in terms of prediction accuracy. The paper points to the growing significance of behavioral and spatial features. However, it did not utilize transformer-based sequence modeling or market-level EV adoption data.

Alam [54] and his colleagues have researched multivariate EV charging demand forecasting using deep learning and machine learning algorithms. Their work focused on a comparison of univariate versus multivariate forecasting. The multivariate forecasting scheme made use of metadata such as charging time, greenhouse gas savings, and gasoline savings. Models that were employed in the study were GRU, CatBoost, RNN, and LSTM. Outcomes indicate that the multivariate approach is better than the univariate method, and GRU is the best-performing out of the compared models for multivariate forecasting. Tolun et al.[18] set up an extensive benchmark for statistical, machine learning, and deep learning approaches for the prediction of EV charging demand. The study utilized monthly EV charging demand data from the Eastern Mediterranean region of Türkiye. Models evaluated during the study were SARIMAX, CNN, XGBoost, GRU, LSTM, Bi-LSTM, and Bi-GRU. Results revealed that deep learning models, notably recurrent neural network architectures such as LSTM, GRU, Bi-LSTM, and Bi-GRU, outperformed classical statistical approaches.What it lacks is that its analysis was restricted to one regional dataset and one forecasting objective, rather than multi-domain charger-type prediction as shown in Table 3.4.

Table 3.4 Recent Deep Learning Studies for EV Charging Forecasting

Study	**Dataset**	**Deep Learning Model**	**Reported Results**	**Review / Limitation**
Koohfar et al. (2023) [45]	EV charging load time-series data with 7-day, 30-day, and 90-day horizons	RNN, LSTM, Transformer	Transformer outperformed ARIMA, SARIMA, RNN, and LSTM	Strong temporal modelling, but no infrastructure or market data
Hussain et al. (2025) [47]	ACN Caltech and JPL charging datasets	LSTM encoder-decoder + Transformer	Caltech: MAE reduced up to 17.27%, MSE up to 19.79%; JPL: MAE reduced up to 24.91%, MSE up to 23.17% at 30 days	Strong hybrid forecasting, but limited to station-level temporal demand

Table 3.4 continued

Study	Dataset	Deep Learning Model	Reported Results	Review / Limitation
Cavus et al. (2025) [53]	Behavioral and spatial EV data from North East and West Midlands, England	Hybrid CNN + XGBoost	HCB-Net achieved higher accuracy than RF, XGBoost, SVM, LSTM, and CNN	Uses behavioral and spatial data, but lacks transformer sequence modelling
Alam et al. (2024) [54]	EV charging data with metadata including charging time, greenhouse gas savings, and gasoline savings	GRU, RNN, LSTM, CatBoost	Multivariate forecasting outperformed univariate forecasting; GRU performed best	Useful multivariate modelling, but limited contextual domains
Tolun et al. (2025) [18]	Monthly EV charging demand data from Eastern Mediterranean Türkiye	CNN, GRU, LSTM, Bi-LSTM, Bi-GRU	Deep learning models outperformed statistical forecasting models	Regional dataset only; no multi-domain fusion

These studies show that deep learning methods raise the accuracy of EV charging prediction by extracting the temporal aspects of data, nonlinear behaviors, and complex interactions of features. Since LSTM and GRU architectures can save information about past charging style changes, they suit very well for the sequential charging data. CNN-oriented architectures are best when spatial or well-organized feature extraction is needed. Also, the self-attention mechanism of Transformer models that enables them to recognize long-range dependencies better than recurrent models is the reason why it is quite the talk of the town in recent years.

3.5 Identified Research Gaps

After analyzing the papers, a number of key research gaps can be drawn from the current body of literature on EV charging prediction.

1. Limited Use of Multi-Domain Data

The majority of published research simply takes one single data source for the analyses, i.e., charging-session records, station-level demand, weather variables, or EV sales data. Classical statistical research mostly depends on historical time-series data, and a number of machine learning and deep learning investigations are centered only on structured charging records. Nevertheless, a whole range of domains that affect EV charging behavior must be taken into account.

2. Insufficient Integration of Behavioral, Infrastructure, and Market Features

Based on the feedback results, it is clear that factors of behavior, infrastructure, as well as factors from the market are generally looked at separately. For instance, when using deep learning techniques, the focus may only be on charging demand during peak hours whereas machine learning algorithms can usually take advantage of the detailed data about station features In fact, charging behavior is almost never put together with charger type, station metadata, and market context within a framework. So it would actually result in wasted opportunity for a model that works across different domains and has potential of drawing in many data sources."

3. Limited Focus on Charger-Type Prediction

Charger-type prediction is vital for planning new infrastructure, rolling out smart charging, and station provisioning in the future. Clearly, this omission suggests a need for a charger-type prediction framework capable of addressing these needs.

4. Weak Modelling of Sequential Charging Behavior

Traditional statistical and machine learning approaches are not powerful enough to adequately model the dependencies between the charging events over a longer time scale. Several deep learning papers use LSTM, GRU or CNN, but only a small number explore using the encoder part of the attention transformer for the modeling of structured sequences of charging events. This missing area has been recognized that it could lead to ideas for how to apply a transformer in this case such as XLM-RoBERTa to the modeling of sequential EV charging behavior.

5. Lack of Cross-Domain Generalization Analysis

Many papers in the field evaluate their models on a single dataset or from one geographical area. Thus, it is hardly possible to conclude whether those approaches would be viable in different charging environments. Cross-domain robustness is a very rare topic even though one might argue whether it should be or not. Only if a paper provides performance of the models not only on single datasets but also when multiple and heterogeneous datasets are involved can one speak of the paper being sufficiently extensive. This is to show how data fusion can lead us to a better generalization.

6. Inadequate Deployment Readiness Assessment

Currently, the researchers tend to be more interested in how well the models can predict which results, not very rarely they consider the implications of deployment readiness.

7. Limited Comparative Evaluation of Different Model Families

Several studies have essentially compared models of a single type, such as statistical methods, machine learning methods, or deep learning methods. However, not many studies have compared model families that are quite different in a lab setting that works equally well for each. Comparing a transformer-based model, a gradient boosting model, and a tabular deep learning model at a time can allow researchers to find their limitations not just in terms of accuracy but also in terms of efficiency, calibration, and suitability for deployment.

3.6 Establishing the Need for the Proposed Research

According to a literature review, it is clear that considerable progress has been made regarding the prediction of EV charging with traditional statistical methods, machine learning, and deep learning. Nevertheless, a great number of existing studies have overlooked several of the most important issues like dependency on single-domain data, weak combination of a variety of information sources, inadequate representation of charging behavior sequences, insufficient or no assessment of model reliability, and concentrating mostly on charging load or energy demand forecasting instead of charger-type prediction.

Such limitations hinder the real-life applicability of the existing prediction models for intelligent charging infrastructure and smart-grid environments.

To address these issues, a well-rounded prediction framework is required that can efficiently incorporate different complementary sources of information and at the same time be accurate, robust, scalable, and ready for deployment. Hence, this study presents a new multi-domain machine learning framework for the prediction of electric vehicle charger types which integrates user behavioral data, charging infrastructure information, and market-level features into a single model. In contrast with past research which almost exclusively depended on a single dataset or one category of learning algorithms, the new approach utilizes three very different model families, XLM-RoBERTa, LightGBM, and TabNet, in order to explore their respective abilities to learn heterogeneous EV charging patterns.

In the context of the suggested framework, XLM-RoBERTa serves as the transformer-based sequence encoder that models charging-event sequences and captures user's long-range temporal dependencies in charging behavior. LightGBM is the choice to effectively perform the non-linear modelling of features related to infrastructure and market, at the same time providing very high computational efficiency with large datasets. TabNet is the attention-based deep learning architecture that is specifically designed for working with tabular data it automatically selects features and makes decisions that can be interpreted.

These are the research goals:

i. Creating a multi-domain integrated learning framework combining behavioral charging profiles, characteristics of electric vehicle charging facilities, and market-level data that would allow prediction of charger types with higher accuracy.

ii. It might be a good idea to investigate different machine learning models such as XLM-RoBERTa Transformer-based sequence learners, LightGBM GradientBoosting models, and TabNet a form of attentive-based deep-learning of tabular data for this task.

iii. Looking at the effects of combining data from various fields by comparing different models using each dataset individually and a multi-dataset combination to see whether mixing different data sources naturally results in a better model performance, a higher level of prediction, and a better overall learning or model.

iv. A framework that can rapidly predict with a high accuracy can be created; this kind of prediction tool will offer a valuable aid in decision-making for planning the smart charging network, regulating the energy demand, and also the integration of the intelligent transportation systems. Such results will not only support efficient planning of charging facilities, efficient management of energy in smart-grids, but also will make the continuous shift to electric vehicles in sustainable traffic systems more effortless.

CHAPTER FOUR

METHODOLOGY

4.1 Chapter Overview

This chapter describes the method behind development, execution, and evaluation of the cooperative Multi-Domain Machine Learning Framework for Electric Vehicle (EV) Charging Forecasting. The methodology has been largely drawn from the requirements to address different aspects of electric vehicle charging data such as charging behavior, charging infrastructure, and market factors. Whereas the majority of traditional approaches rely on just one source of information, the idea of the new multi-source framework enables an overlay between different datasets thus allowing not only a better prediction but in terms of robustness.

The methodology in its entirety involves several steps that are executed in sequence. It commences with research design and dataset acquisition, then proceeds with data preprocessing, feature engineering, multi-domain data fusion, development of machine learning model, model training, evaluation, reliability assessment and ends with deployment readiness analysis. Each step has been carefully and thoroughly outlined. Such a way of planning the development would yield a framework that is flexible, scalable, maintains itself with minimal effort and can cope even with very dissimilar data inputs.

Initially, we gathered three publicly available electric vehicle charging behavior, charging network and car market datasets, respectively. As these datasets are rather heterogeneous in terms of structure, characteristics, time granularities and geographical details, we invested quite a bit in making the datasets fit and clean each other, data harmonization. Beside the missing data, duplicates, various types and forms of files and extraordinary values that are identified in the data cleaning phase of the data, each of these points will be handled thoroughly in order to get a level that the resulting clean data justify data-driven decisions.

Feature engineering methods are generally applied post cleaning to add new features/attributes that characterize (1) temporary aspects (i.e., the time element) (2) spatial aspects (i.e., location element) (3) behavioural aspects (e.g., how someone uses a car or charger) and (4) infrastructure (e.g., Size, number and other characteristics of EV charging stations). These attributes may become strong predictors of EV charging behavior.

Then the features developed in the previous step will be joined via the multiple-domain data integration method, which preserves the original meaning, eliminates the redundant information, and maintains as much of the information as possible.

The integrated data set becomes the input of various highly-different machine learning methods that we run to train our prediction models.

- Machine learning model 1 XLM-RoBERTa: the transformer-based deep learning model that focuses on capturing sequential pattern changes in one or several time periods of EV charging.

- LightGBM: this is a gradient boosting decision tree that works best on structured tabular data.
- TabNet: this uses an attention mechanism and is deep learning specifically tailored to heterogeneous tabular datasets.

The selection of a two-phase training plan stems from the need of exploring both domain-specific learning capacity and cross-domain generalization. Hence, at the first phase, a single dataset is employed to build the model that will be able to predict based only on the domain. At the second phase, all the datasets are combined into one multi-domain dataset that shall allow the models to learn complementary information from the behavior, infrastructure, and market perspectives at the same time.

To compare model performance, a wide variety of classification and statistical metrics have been used for research and experiment, for example, Accuracy, Precision, Recall, F1-score, Macro F1-score, Weighted F1-score, Receiver Operating Characteristic (ROC) curves, Area Under the Curve (AUC), and confusion matrices. Setting aside prediction accuracy, confidence score distributions and reliability analyses are done in order to measure prediction certainty and calibration quality. These go a long way to enhancing the trustworthiness of the proposed framework for its practical real-world deployment.

The ability to deploy systems in the field is definitely one of the topics investigated regarding the system efficiency considering computation, the time for inference, scalable factors like computation resources, memory needs, robustness features, and the simplicity of incorporating an intelligent real-world EV charging management system.

4.2 Research Design

The research methodology is divided phase by phase detailing the creation and testing of a multidomain machine learning framework. The strategy unites multiple subfields of machine learning through the development of practical solutions to real-life problems. The research is a purely quantitative experimental study conducted predominantly by collecting, linking, and analyzing EV charging datasets using machine learning techniques. One of the main problems highlighted in the problem definition is the fact that most current EV charging predictions use a single dataset, thereby restricting accuracy.

This research next compiles three different datasets that have charging station-specific information. The first dataset, the Forecasting of EV Charging, gives an idea of how much load the stations will be able to bear during different times of the day, so that it may be possible to figure out whether a certain type of charging station will be able to cater to future demands when the appropriate forecasting data has been used as a guide. The second dataset, named the EV Charging Patterns set, contains information on user habits, station locations, infrastructure details, time and place data, and demographics of different areas. The third one is a global EV Charging Stations database that is freely available and covers the thousands of EV charging stations worldwide, such as their location, capacity, type, availability, market behavior, etc. After that, this work focuses on basic data cleaning, i.e. resolving problems such as missing data, removing duplicates, fixing timestamp errors, relabeling codes, and discarding suspicious or extreme observations.

Moving further, the paper aims at discovering key features that may help in solving the problem. Mostly, such features are time-based, demographic-based (e.g. age, income, gender), infrastructure-based (number of charging devices, availability of fast chargers) and market-based. This work integrates all data sources into a unified framework, thereby creating a multi-domain data fusion that is not trivial to accomplish but has been managed through strategies such as geographical matching, temporal alignment, station-based matching, and semantic matching.

The next stage includes the training and benchmarking of three Machine Learning Models: XLM-RoBERTa (a transformer-based architecture), LightGBM (a gradient boosting technique), and TabNet (deep neural networks trained on a database with lots of tables). In terms of methods, this paper covers the field of transformers, gradient boosting as well as tabular deep learning. Finally, we measure and verify the performance of these forecasting models for charge demand in e-vehicles by using metrics like Accuracy, Recall, F1-score, ROC-AUC, and Precision, including assessments for time of training, the speed of prediction, and also the models' capacity to scale.

4.3 Proposed System Architecture

The design of the framework comprises six stages: data collection, data cleaning, feature extraction, the integration of multi-domain datasets, model training and performance assessment. Data collection is performed by acquiring three public datasets that have then been transformed, cleaned, and standardized via several steps including removing missing values, removing outliers, categorical encoding, feature scaling, and temporal feature extraction in a sequence. After the datasets are processed, they are merged by feature harmonization and spatial alignment into a wide multi-domain dataset. In an attempt to investigate the potential value brought by multi-domain learning, the three selected models, XLM-RoBERTa, LightGBM, and TabNet, are trained on the basis of both individual datasets and the unified dataset shown in Figure 4.1. The models are then benchmarked based on the following metrics, Accuracy, Precision, Recall, F1-score, ROC-AUC, confusion matrix analysis, confidence calibration, and computational efficiency.

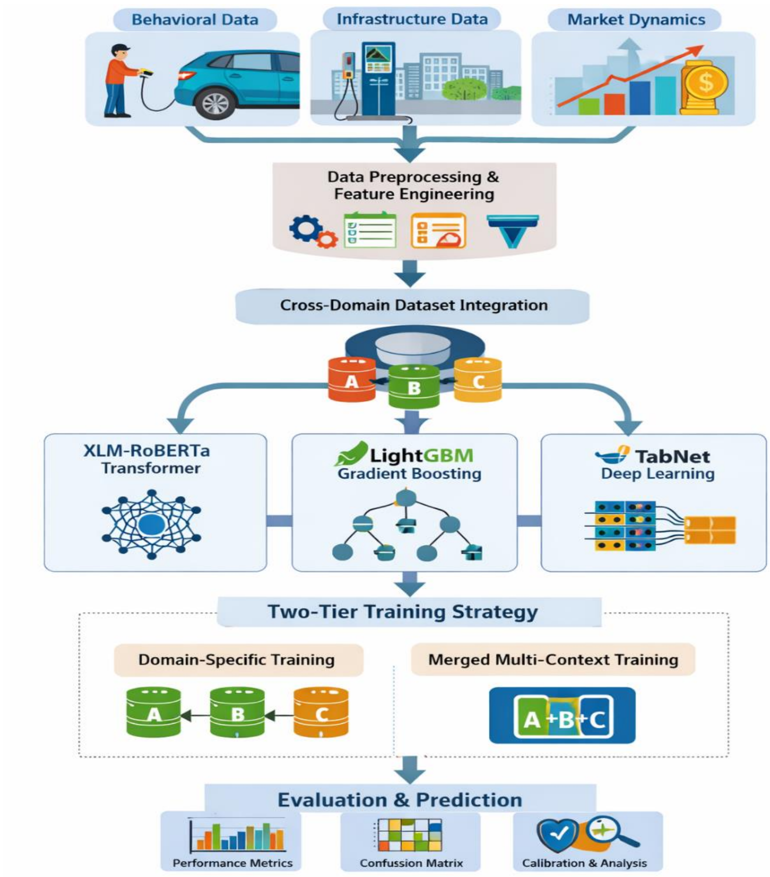


Figure 4.1: The proposed Architecture diagram

4.4 Dataset Description

The paper therefore introduces a dataset-based strategy that spans multiple domains, using three open datasets where each dataset highlights one aspect of the EV charging ecosystem, to establish a unified learning framework. We combined these datasets to overcome each other's limitations and get a more detailed picture of users activity, infrastructure, and market context that varied a lot mention in Table 4.1.

The EV Charging Forecasting Dataset is mainly about users of individual charging sessions and their characteristics. The EV Charging Patterns Dataset is about how vehicle use is planned and charging activity over time. The Global EV Charging Stations Dataset is mostly about metadata as well as features such as location geography, and site features of charging points.

Table 4.1 Dataset Description

Dataset	Domain	Number of Records	Major Features	Purpose
EV Charging Forecasting Dataset	Charging Behavior	2,274	Charging duration, energy consumed, session timestamps, user information	Learn charging session behavior
EV Charging Patterns Dataset	User Behavior	1,320	Vehicle type, battery capacity, charging duration, energy consumption, charging location	Learn temporal charging patterns
Global EV Charging Stations Dataset	Infrastructure	~5,000	Station ID, charger type, latitude, longitude, station capacity, operator, status	Learn infrastructure characteristics

4.4.1 EV Charging Forecasting Dataset

The EV Charging Forecasting Dataset is the fundamental behavioral dataset used throughout the study. It is a compilation of detailed logs or records of charging sessions of electric vehicles, which can also be used for predicting charging demand. Each line in the file corresponds to a charging session and contains session identifiers, connection/disconnection time, charging duration, energy, user data, and pricing features among others.

There are 2, 274 charging sessions in the dataset with 34 attributes that describe various aspects of charging activities. The timestamp information helps to derive time-related features such as charging hour, day of week, weekend indicator and peak charging time. On the other hand, charging duration and energy consumption give further details about the level of charging and user behavior

Since this dataset represents actual charging sessions as opposed to simulated observations, it is highly suitable for modeling charging demand. This will therefore be the main data source for understanding behavioral charging characteristics in the proposed framework.

4.4.2 EV Charging Patterns Dataset

The EV Charging Patterns dataset presents information on users' charging behavior and the corresponding time frames. A dataset such as this was released before mainly for predicting the number of charging sessions. Here the intention is different and it is the relationship between the various factors that decides how a customer feels about a car charging in different types of situations.

The datasets have about 1, 320 charging records with close to 20 attributes, such as battery capacity, charging duration, energy consumption, travel distance, vehicle type, charger type, charging station category and user type. Understanding these variables can lead to the segmentation of charging behavior that is correlated to different types of vehicles and users.Being able to show variations of a temporal demand pattern from one time to another and from one day to another is a significant feature of this database.

This kind of pattern extraction helps the machine learning algorithms to better understand the regularities in the charging process and thus, to make their predictions more accurate.

4.4.3 Global EV Charging Stations Dataset

The Global EVCDS represents location as well as infrastructure details of EVCC's (Electric Vehicle Charging Centre/Centre). It's the opposite of datasets about charging behavior or usage that this one deals only with charging centers' features instead of individual charging events.

In this way, the dataset can show roughly how 5 different, 000 charging centers have been identified with each given station id, latitude and longitude, address, city, country, kind of charger, kind of connector, type of charging, number of stations, operator, and also state of the station.

Accessibility of infrastructure is one of the main determinants of charging demand. Station density, charging capacity, charger location and kind of technology have a major effect on the way people use the chargers. With the help of the characteristics of electric vehicle chargers' infrastructure, the proposed model will be able to determine the connections between the number of vehicles coming to charge their batteries with the proximity, number, and availability of the EV stations.

4.4.4 Dataset Characteristics

Although all three datasets are about the same subject area they differ significantly in their depth of detail, in the types of features they provide and in the scopes of topics they address. Behavioral data, on the one hand offer data mainly at session-level to describe charging activities while infrastructure data on the other hand collect metadata describing charging station at station-level to reflect the physical characteristics of the stations.The differences also extend to the temporal and spatial resolution.

Behavioral data records the details of each charging session even at the time-stamp level while most infrastructure data is relatively stable and it describes the characteristics of charging stations over a prolonged period. These inconsistencies complicate a direct merging of the datasets yet they also produce information that can be used together through proper processing and alignment of features. The main features of all three datasets can be found on Table 4.2.

Table 4.2 Comparative Characteristics of the Datasets

Characteristic	Forecasting Dataset	Charging Patterns Dataset	Charging Stations Dataset
Domain	Charging Sessions	User Charging Behavior	Charging Infrastructure
Data Level	Session	Session	Station
Temporal Information	Yes	Yes	Limited
Geographic Information	Partial	Partial	Complete
Infrastructure Information	Limited	Moderate	Extensive
Behavioral Information	Extensive	Extensive	Limited

4.4.5 Dataset Combination Rationale

Each dataset offers a unique angle that can enhance the machine learning model prediction we want to construct. The EV Charging Forecasting Dataset helps us learn about the charging sessions aspects, the EV Charging Patterns Dataset includes temporal information together with users' detailed behavior, while the Global EV Charging Stations Dataset sheds light on the facility as well as location issues. Through this approach of merging very different datasets our method would be able to forecast EV demand much better than if it would base forecast on only one kind of data.

Cutting the three layers of users', technology', and market' data will be the first step for the algorithm, then the integration will be done with the ML technique in such way that not only we discover underlying relations between customers' charging habit, station availability, geographical factors and the level of EV demand but also we obtain a higher performance than if we had only used one machine learning model. This multidisciplinary approach for machine learning is expected to be very robust, scalable, and flexible when the model continues processing unseen data.

4.5 Data Preprocessing

Among the determining factors in ensuring the success of machine learning model development is data preprocessing as the quality of input data has a direct effect on the model's performance and ability to generalize. Due to unaligned feature names, data types, time intervals and distributions of attributes, combined with presence of missing values, duplicate records and not only, data from various public sources, which were the ones used in the experiments here, were especially difficult to clean and merge. Hence, the need of a thorough preprocessing pipeline to prepare the raw data for multi-domain machine learning by introducing standardization, cleaning, and suitable formatting.

One important point we should note is that the preprocessing pipeline strives to extract individual characteristics of each dataset to keep the domains apart, yet the idea was to keep the data flowing with each other or in other words, achieve consistency of the whole data series. The entire data preprocessing stages used in this work are shown in Figure 4.2.

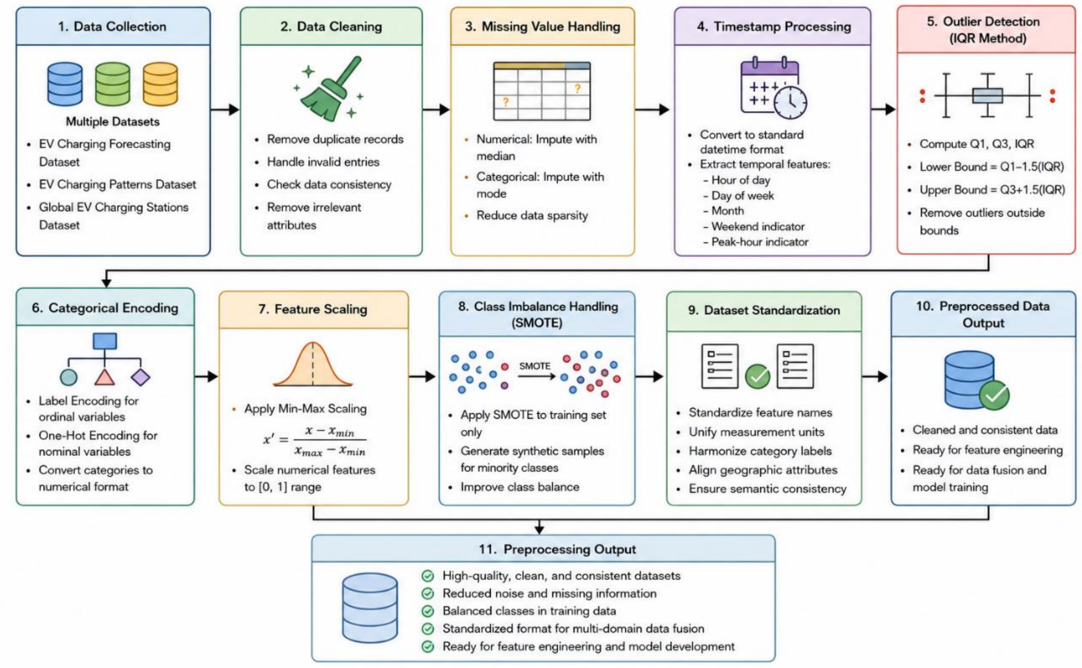


Figure 4.2: Overall preprocessing workflow

4.5.1 Data Cleaning

The first phase of preprocessing was the cleaning of each dataset through detection and correction of inconsistencies. Duplicate entries were eliminated to get rid of repeated charging sessions and station information that could lead to biased model training. Incomplete or invalid ID records, in addition to other unusable data, were discarded, and missing values were dealt with by using different imputation methods depending on the type of feature. We used the median to fill in missing numeric values since the mean is heavily influenced by outliers while the median is not. For the categorical features, the missing values were imputed with the class that occurred most frequently. This data preprocessing not only made the database more filled out but also maintained the original data's statistical characteristics.

4.5.2 Handling Missing Values

The lack of complete data in real-world charging datasets may result from many factors such as faulty sensors, communication interference during charging, and variations in data gathering methods. This study has chosen not to discard all incomplete records, but instead has used feature-specific imputation methods to reduce the loss of information.

For a numerical feature x, missing values were replaced using the median value as follows:

$$\begin{cases} x_i & if \;\; x_i \; is \; availabl \\ x & \end{cases} \tag{4.1}$$

4.5.3 Duplicate Record Removal

Duplicate charging sessions may be recorded if the charging stations keep sending the same session logs multiple times or different datasets are brought together from various repositories. Such duplication leads to overestimation of certain charging pattern occurrences; thus, the model may get biased.

Each dataset was looked at by using unique identifiers like:

- Session ID
- Station ID
- Timestamp
- Vehicle identifier

The duplicates were deleted only after the first instance of each record was saved.

4.5.4 Timestamp Standardization

The three datasets have timestamp fields that have been saved in different formats. Since temporal data are very important for predicting charging demand, all timestamps were changed to a single datetime format.

After timestamp conversion, some temporal features were derived, such as:

- Hour of day
- Day of week
- Month
- Weekend indicator
- Peak-hour indicator

The length of a charging session can be expressed as

$$Charging\ Duration = End\ Time - \ Start\ Time \tag{4.2}$$

Where

- Start Time is the time when the charging session was started
- End Time is the time when the charging session was finished.

4.5.5 Outlier Detection and Removal

Around a big part of real-world charging datasets includes abnormal data because sensors can fail, communication goes wrong, or one can enter the data wrong. Examples of abnormal data points include very long charging sessions, negative energy consumption values, and super-long charging durations. This paper uses the Interquartile Range (IQR) method to detect outliers, as a technique to keep the influence of such abnormalities under control. Lower and upper limits were calculated as

$$\text{Lower Bound}=Q1-1.5(IQR) \tag{4.3}$$

$$\text{Upper Bound}=Q3+1.5(IQR) \tag{4.4}$$

Besides, Q1 is the first quartile, and Q3 is the third quartile

Data points or observations that went beyond these limits were deemed as outliers and then they got removed from the data set just before the model training. This approach was actually beneficial as it not only helped in eliminating the most of the noise present in the data but also left us approximately with only the charging records that can be described as valid.

4.5.6 Categorical Feature Encoding

It is a good idea when working with machine learning models to make sure that all inputs are numeric only. For this reason, all categorical variables were transformed into their corresponding numeric formats. Below are the two encoding methods that we applied:

i. Label Encoding, for example, was used to represent charger levels as ordinal data.

ii. One-Hot Encoding was used for nominal variables, which included:

Vehicle type, Charger type, Station operator, User category, Charging location, Vehicle type, Charger type, Station operator, User category, charging location

This approach allowed the model to incorporate these categorical features during training, ensuring the model does not inadvertently assign a false hierarchy to category labels.

4.5.7 Feature Normalization

There are features in the data that are measured in very different units/ scales. Here are some examples:

- Charging length in minutes
- Energy consumption in kWh
- Battery size in kWh
- Location coordinates
- Number of charging points

Optimization algorithms can be influenced in a negative way by features with widely different magnitudes. This is especially true for deep neural networks.

Therefore, numerical features were normalized using Min-Max Scaling, defined as

$$x \quad \frac{x - x_{min}}{x_{max} - x_{min}} \qquad 4.5$$

Where

- x is the original value
- x′ is the normalized value
- $x_{max} - x_{min}$ Denotes the minimum and maximum values of the feature.

By normalizing the data, we ensure that numerical features of the variables have the same weight when the model is being trained.

4.5.8 Class Imbalance Handling

The ratio of different charger types in the datasets was not quite equal. Some charger categories had very few cases in comparison with others that were well represented. This situation might cause the model to be trained to the majority classes because of the bias. The issue was fixed by applying the Synthetic Minority Over-sampling Technique (SMOTE approach) exclusively to the training subset. With this method, examples from underrepresented groups are generated by blending features from existing samples and their closest neighbors. This results in increased class balance of the data and prevents the mere copying of records. It is important to mention that oversampling was done exclusively on the training data. Validation and testing sets were kept unchanged, thus, to enable fair evaluation of model performance.

4.5.9 Dataset Standardization

Due to the origin of the three datasets in different domains, they were using different feature names and measurement units.

To let them work together, feature standardization covered:

- Changing the names of variables that mean the same
- Converting measurement units to the same standard
- Making timestamp formats the same
- Standardizing charger types
- Standardizing vehicle types
- Adjusting geographic features

If they do these, they ensure the datasets convey the same meaning.

4.6 Feature Engineering

Feature engineering plays an important part in the research methodology presented, as the success of machine learning models hinges on the quality and relevance of the features fed to the learning algorithm. The raw electric vehicle (EV) charging data, on the other hand, is typically heterogeneous as it is collected from different sources of charging session records, infrastructure databases, and market-related data. These sources of data record different types of attributes such as temporal, spatial, numeric, and categorical. To make this information suitable for model training, these attributes must first be transformed appropriately. The main aim of feature engineering for this paper is to map different types of raw data points into one feature space that represents the charging behavior of the user, the characteristics of the charging infrastructure, and the market conditions accurately.

4.6.1 Temporal Feature Engineering

The temporal aspect is one of the crucial factors of EV charging prediction since charging demand has a huge variation depending on the hour of the day, day of the week, seasons, and holidays. Charging activities usually follow the rhythm of users' commuting, such as charging at work and charging at home. Hence, several temporal features have been identified from the timestamp information contained in the charging session dataset.

The original timestamp was broken down into multiple informative temporal attributes such as:

- Year of the charge
- Month of the charge
- Charging day
- Weekday
- Charging time
- If it is a weekend or not
- If it is a working hour or not
- Season

By providing these engineered features to the prediction models, they can learn charging patterns at the daily, weekly, and seasonal levels, which are impossible to extract from raw timestamps shown in Table 4.4.

Table 4.3 Temporal Features Extracted

Feature	Description	Purpose
Hour	Hour of the charging session	Captures daily charging patterns and time-of-day variations.
Day of Week	Day of the week (Monday–Sunday)	Learns weekly charging behavior and usage trends.
Month	Calendar month	Captures monthly and seasonal variations in charging demand.
Weekend	Binary indicator (Weekday = 0, Weekend = 1)	Distinguishes charging behavior between weekdays and weekends.
Peak Hour	Peak or off-peak charging period	Models electricity demand fluctuations during peak and non-peak hours.
Season	Spring, Summer, Autumn, Winter	Captures long-term seasonal effects on EV charging behavior.

4.6.2 Behavioral Feature Engineering

Behavioral features reflect the manner in which electric vehicle (EV) users are engaged with the charging infrastructure. These variables essentially depict charging behavior and rank among the most potent features for the task of charger-type identification. Records of charging sessions were converted into behavioral features that encapsulate the essence of user charging patterns, as shown in Table 4.5.

Table 4.4 Behavioral Features

Feature	Description	Purpose
Charging Duration	Total charging time	Measures the length of each charging session and reflects charging behavior.
Energy Delivered	Energy consumed during the charging session	Quantifies the amount of electricity delivered to the EV.
Average Charging Power	Energy delivered divided by charging duration	Represents the average charging rate during a session.
Arrival Time	Charging session start time	Captures the time at which the vehicle begins charging.
Departure Time	Charging session completion time	Indicates when the charging session ends and the vehicle disconnects.
Session Frequency	Number of charging sessions	Measures how frequently a vehicle is charged over a given period.
Charging Interval	Time between consecutive charging sessions	Captures charging regularity and user charging habits.

4.7 Infrastructure Feature Engineering

Infrastructure features mainly refer to the tangible aspects of the charging stations and their equipment. These features reveal the context of charging conditions, such as availability, station capacity, and charger properties shown in Table 4.6. The infrastructure dataset was transformed into features suitable that comprised:

- Type of charger
- Type of connector
- Highest charging power
- Count of charging ports
- Location in terms of latitude and longitude
- Station size or capacity
- Operator of the network
- Whether the charging station is public or private

Categorical infrastructure variables were encoded using label encoding, while numerical variables were first standardized and then passed on for the model.

Table 4.5 Infrastructure Features

Feature	Description	Purpose
Charger Type	AC Level 1, AC Level 2, or DC Fast Charger	Identifies the charging technology and its charging speed.
Connector Type	CCS, CHAdeMO, Type 2, Tesla, etc.	Specifies the connector standard compatible with different EV models.
Maximum Power	Rated charging power (kW)	Represents the maximum power output available from the charger.
Number of Ports	Number of available charging connectors	Indicates the station's ability to serve multiple vehicles simultaneously.
Latitude	Geographic latitude of the charging station	Identifies the station's north–south geographic position for spatial analysis.
Longitude	Geographic longitude of the charging station	Identifies the station's east–west geographic position for spatial analysis.
Station Capacity	Total charging capability of the station	Represents the overall charging capacity available across all charging ports.

4.7.1 Market Feature Engineering

In fact, market variables reflect not only the EV supply chain but also the demand for charging on a regional level. The combination of changes in charger utilization with swings in the rate of EV adoption, different levels of planned infrastructure, policy support, etc. The market dataset includes a few more market features among the list of explanatory variables:

- Size of the regional EV stock
- Number of charging stations per unit area
- Concentration of population

- Degree of urbanization
- Regional level of electricity usage
- The pace of growth in the EV market

These features give the model the opportunity to take into account the big-picture level of the changing external environment that complements the behavior during charging sessions and the characteristics of the infrastructure mentioned in Table 4.7.

Table 4.6 Market Features

Feature	Description	Purpose
EV Registrations	Number of registered EVs	Represents EV adoption level in a region.
Station Density	Charging stations per region	Measures charging infrastructure availability.
Population Density	Population per square kilometer	Captures regional demand potential for EV charging.
Urbanization	Urban/rural classification	Distinguishes charging patterns across urban and rural areas.
Market Growth	Annual EV growth rate	Captures expansion trends in the EV market.

4.7.2 Categorical Feature Encoding

Some of the predictor variables contained categorical (text-based) information. Due to the fact that most machine learning models are unable to operate on this type of data directly, it necessitated the use of Label Encoding, representing categorical variables as numbers. This approach assigns unique integers to each category, ensuring that computational efficiency remains unaffected.

4.7.3 Feature Scaling

Numerical features have been min-max normalized so that differences in scale will be less of a factor, and also the model can get a better chance to converge. By normalizing the min and max of standardization, one can prevent the model from being influenced by features that have huge magnitudes. Besides helping interpretation and visualization, it also gets training done sooner since fewer iterations would be needed to get to convergence.

4.8 Multi-Domain Data Fusion

This thesis presents a large machine learning system that was created by integrating different heterogeneous datasets collected from various publicly accessible sources to predict EV charger types. Each dataset on its own provides useful but incomplete information about the EV charging ecosystem. Therefore, the multi-domain dataset integration approach was introduced not only to assemble behavioral charging records and charging infrastructure data but also to include market-level information in a single analytical dataset.

Uncharacteristically, this paper does not work on one data source, which is the usual case of traditional EV charging prediction studies, but instead the data from various domains is pooled together. Through the merging, one could not only raise the standard of the predictions but also enable the models to better understand the situation. The behavior datasets reflect the user's charging behavior; the infrastructure datasets indicate the physical characteristics of the charging stations; the market datasets show the EV consumption level and the charging network in the region. When these datasets are fused, machine learning models are able to uncover the dependencies that each dataset alone could not disclose.

Data integration was the first of five processes that followed each other in the course of data preparation: data standardization, schema harmonization, temporal synchronization, spatial matching, and feature merging. Figure 4.2 shows the whole process of multi-domain dataset integration in detail.

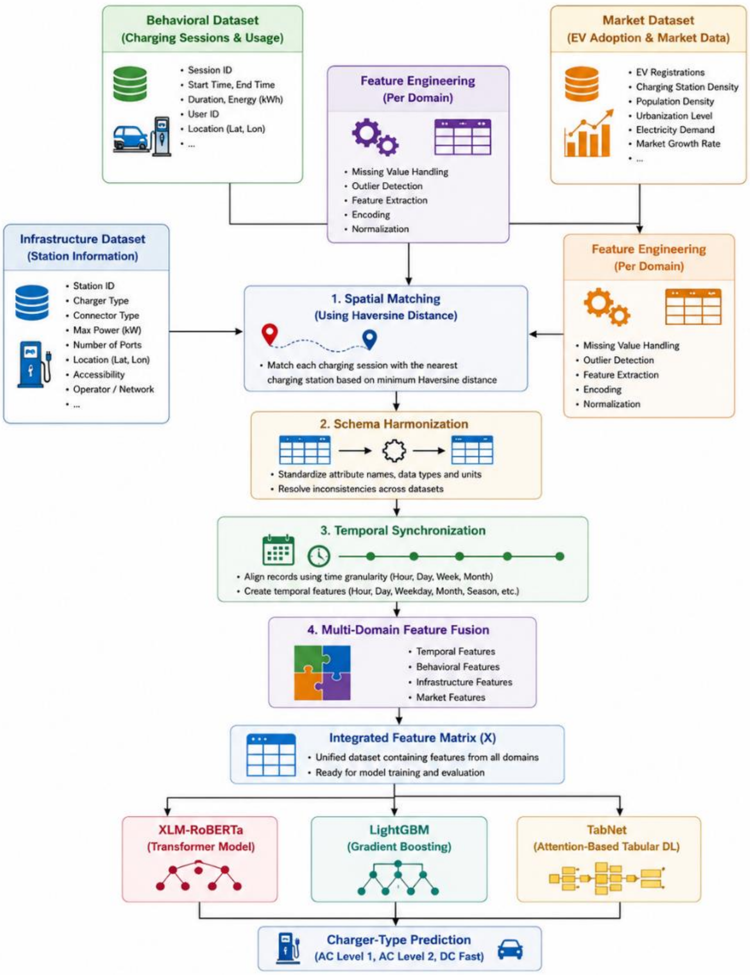


Figure 4.3: Proposed Multi-Domain Dataset Integration Framework

4.9 Proposed Model Architectures

The suggested multi-domain machine learning framework utilizes three separate learning methods to forecast the types of electric vehicle (EV) chargers based on various user behavior, infrastructure, time, and market information sources. The chosen models include three different machine learning paradigms, i.e., transformer-based deep learning, gradient boosting decision trees, and attention-driven neural networks for table-structured inputs. By mixing these diverse learning methods, the suggested framework investigates how different model structures decipher complex correlations in multi-domain EV charging data and determine the best method for charger-type prediction in the real world. The reason behind the choice of models was their proven efficiency in dealing with different data traits. Transformer models are outstanding at sequential learning and discovering latent information in ordered data. Gradient boosting provides highly accurate results at a lower cost of time and resources for structured datasets with complex feature interactions. Tabular neural networks with attention can highlight the most informative features whilst being interpretable and scalable. As the unified dataset used for this work combines both sequential behavioral information and structured tabular attributes, studying these complementary architectures provides an exhaustive evaluation of their prediction power. Going one step further than traditional EV literature that is mostly limited to an intra-family model comparison, this study compares three entirely different architectures on a level playing field (i.e., identical data pre-processing, feature engineering, model training, and testing).

Each model receives the same integrated feature matrix obtained from the multi-domain dataset integration stage, ensuring that differences in performance are only due to the model learning mechanisms and not to the input data used. This approach makes it possible to perform an unbiased comparison in terms of predictive accuracy, computational efficiency, robustness, and deployment readiness.

The three prediction models implemented in the proposed machine learning framework are:

4.9.1 XLM-RoBERTa

As the transformer for the proposed framework, XLM-RoBERTa is used. The model is trained to represent charging-event sequences and to recognize charging behavior's long-range dependencies. Thanks to the self-attention method, XLM-RoBERTa captures contextual relationships among charging sessions that traditional machine learning methods fail to realize. The detailed design and execution of XLM-RoBERTa are shown in Figure 4.3

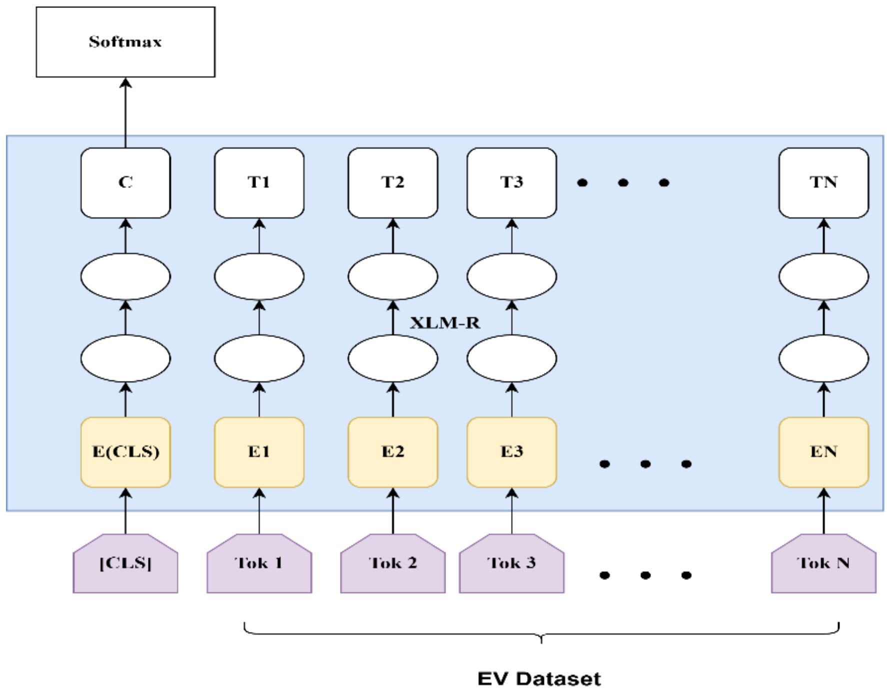


Figure 4.4: XLM-RoBERTa Architecture

4.9.2 LightGBM

LightGBM (Light Gradient Boosting Machine) is the gradient boosting model that we have chosen for our research. We trained LightGBM with the multi-domain integrated dataset that we have designed, which integrates behavioral charging data, temporal features, charging infrastructure characteristics, and market-related information. Our LightGBM model can accurately capture the interactions of different features within the data due to its histogram-based decision tree learning algorithm combined with a leaf-wise tree growth strategy. The model also has low computational costs. This method's ability to process high-dimensional structured data, to handle large-scale datasets, and the provision of quick training and inference have made it especially suitable for intelligent EV charging prediction applications.

LightGBM is considered within the proposed framework as the representative gradient boosting model, and it establishes a computationally efficient baseline for the comparison of the transformer-based XLM-RoBERTa model and the attention-based TabNet architecture.

This thesis will talk about the mathematical modeling, algorithm, and the general architecture of the model in the LightGBM paper in the forthcoming sections.

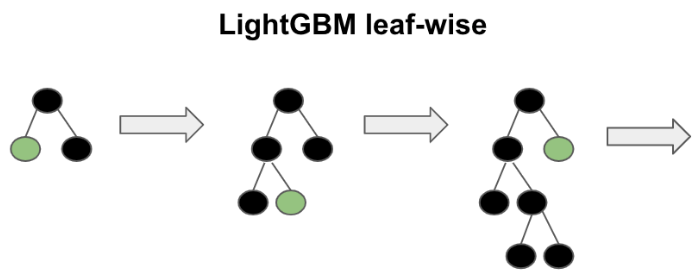


Figure 4.5: LightGBM Architecture

4.9.3 TabNet

TabNet is a deep learning technique based on an attention mechanism used by us to get insights into the proposed multi-domain integrated dataset that combines behavioral charging data, time aspects, charging facilities, and market-related information. Traditionally, deep neural networks treat all features equally, whereas TabNet operates through a sequential attention mechanism that, at each decision step, picks the features that are most informative via attentive transformers. By consistently updating which features it uses, the model focuses only on the most useful characteristics, which leads to higher prediction accuracy, makes the model's results easier to interpret, and helps it learn more effectively from mixed tabular data. Automatically discovering significant feature interactions is one of the reasons why TabNet is very efficient for complicated EV charging prediction problems with large and high-dimensional structured datasets.

Figure 4.5 shows the detailed design of the proposed Multi-Domain Machine Learning Framework. Various datasets, including behavioral, temporal, charging infrastructure, and market-related data, are first subjected to cleaning, transformation, and selection of relevant features. Afterward, multi-domain data integration takes place resulting in a single feature matrix. The consolidated feature representation is then given at the same time to three separate machine learning models: XLM-RoBERTa, LightGBM, and TabNet. The three models each discover different nonlinear relationships among the features and produce separate predictions regarding the type of EV charger using different learning approaches.

The models were subjected to the same experimental test setup with different performance metrics: Accuracy, Precision, Recall, Weighted F1-score, Macro F1-score, Receiver Operating Characteristic Area Under the Curve (ROC-AUC), Confusion Matrix Analysis, Confidence Calibration, Computational Training Time, in order to assess their predictive capability to the fullest.

A further optimized method, i.e., a combination of prediction outputs of the three models via weight optimization, is examined as another possible ensemble technique to improve and stabilize our results in order to reach the highest level of classification reliability. The model comparison allows to identify the ideal one that balances between high predictive accuracy, robustness, computational efficiency, and the readiness for deployment in the field of intelligent EV charger-type prediction and smart charging infrastructure management.

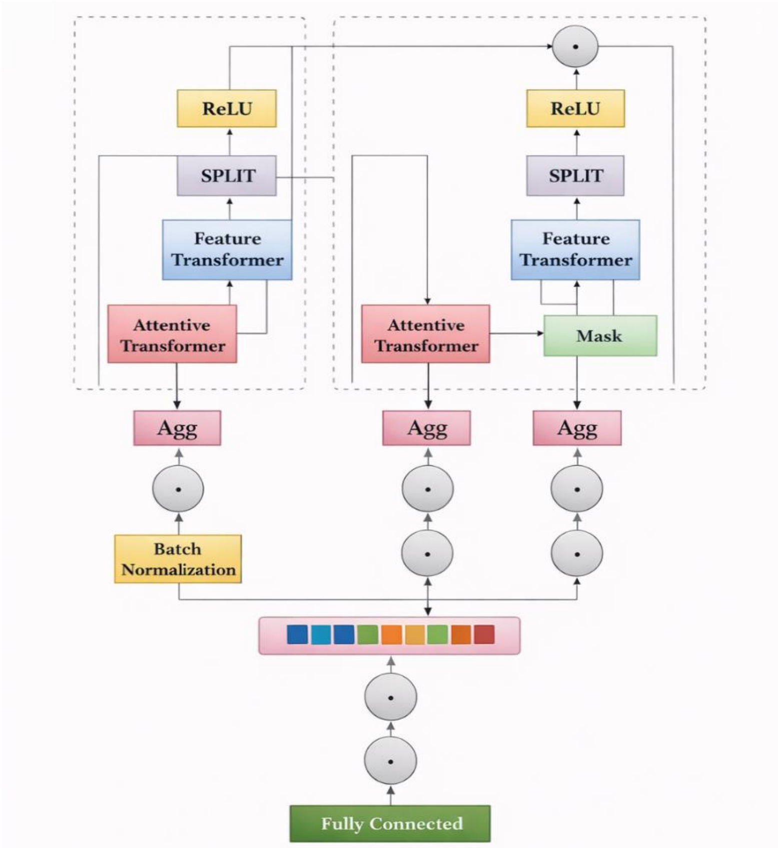


Figure 4.6: TabNet Architecture

4.10 <u>Model Training Setup</u>

Data preparation, feature engineering, and the integration of multiple datasets from different domains all end in one final product, the processed dataset. This dataset became a raw material for training three machine learning models we had proposed: XLM-RoBERTa, LightGBM, and TabNet. To avoid any bias in the performance comparison of the models, a consistent training schedule was employed for all three. Through a stratified sampling method, 70% of the integrated dataset was allocated for training and 30% for testing to maintain the distribution of charger-type labels. Also, to enhance the generalization ability of the model and avoid overfitting, 5-fold stratified cross-validation was carried out for model creation and hyperparameter optimization.

Each model underwent training separately but with the same training data, target labels, and evaluation methods. XLM-RoBERTa was fine-tuned with the AdamW optimizer in conjunction with the cross-entropy loss function, which was helpful to the model in learning sequential charging behavior through transformer-based self-attention.

LightGBM was developed based on its histogram-based gradient boosting technique with leaf-wise tree propagation to effectively learn nonlinear associations from structured multi-domain features. TabNet was developed based on the idea of sequential attention and hence displays feature selection on its own and at the same time shall have the ability to learn heterogeneous tabular data. The model which proved to be the best during validation was finally picked and then it was subjected to evaluation by means of the independent testing dataset.

Model's diagnostic performance was measured by a battery of standard metrics, including Accuracy, Precision, Recall, F1-score and its variations (Macro, Weighted), Receiver Operating Characteristic Area Under the Curve (ROC-AUC), confusion matrix, and confidence calibration.

The architected solution was realized using Python 3.11 as the programming platform in the Jupyter Notebook environment. Open-source packages for almost all tasks, with very few missing (data preparation, model building and training, performance evaluation), were used. On top of the abstraction layer that Pandas provides over raw data for easy manipulation, NumPy was used for operations involving numeric data. Scikit-learn was the main tool for preprocessing, data splitting, and metric gathering.

PyTorch and Hugging Face Transformers are an excellent duo for deploying and adapting the XLM-RoBERTa model, while LightGBM is the go-to tool for gradient boosting classification. PyTorch-TabNet facilitates the implementation of the TabNet design, and visualization is handled by Matplotlib along with Seaborn. SciPy, being the final very versatile tool from the main set, is used for scientific computation. Together, these packages deliver the power and scalability necessary for state-of-the-art algorithms and also enable the reproducibility of experimental research.

The experimental study took advantage of a particularly powerful desktop: Intel Core i7 (12th Generation or equivalent) as the processor, 32 GB DDR4 RAM, and NVIDIA RTX 3060 12 GB for transformer-based model training acceleration. Microsoft Windows 11 (64-bit) as the operating system, and where applicable GPU acceleration for deep learning with CUDA were also available. This hardware estate served perfectly for preprocessing large multi-domain datasets, building transformer-based and deep learning models, and carrying out fully-fledged experimental evaluation.

4.11 Evaluation Metrics

The model's effectiveness was evaluated using various metrics to obtain a comprehensive assessment. The performance of the proposed multi-domain machine learning framework was tested through several quantitative evaluation metrics to provide a thorough evaluation of the predictive power of the built models. Since EV charger-type prediction is posed as a multi-class classification problem, basing on a single metric such as classification accuracy may give a partial evaluation, especially when the class distribution is not balanced. Hence, at least two evaluation metrics were used to assess different facets of classification performance that include the overall correctness, class-wise prediction capability, robustness, discrimination ability, and prediction reliability.

Some of the metrics applied in this research include: Accuracy, Precision, Recall, F1-score, Macro F1-score, Weighted F1-score, Receiver Operating Characteristic Area Under the Curve (ROC-AUC), Confusion Matrix, and Confidence Calibration. Altogether, these metrics offer a thorough evaluation of the effectiveness of the model and will allow a fair comparison between XLM-RoBERTa, LightGBM, and TabNet.

4.11.1 Accuracy

Represents the overall classification correctness by dividing the count of accurate predictions by the full set of predictions made [55]. When the classes are balanced, a higher value means the model is successfully identifying a bigger share of the samples, making it a reliable indicator of performance, as shown in Equation (4.6).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{4.6}$$

4.11.2 F1-Score (Weighted)

Weighted F1-score is defined as the weighted harmonic mean of precision and recall, with each class's result weighted according to its frequency. [56]. A higher weighted F1 score reflects that the model performs consistently well across all groups, rather than just excelling in the most common category, as illustrated in Equation (4.7).

$$F1 - Score(weighted) = \frac{2\sum(Precision_i \times Recall_i \times Support_i)}{\sum(Precision_i + Recall_i) \times Support_i)} \tag{4.7}$$

4.11.3 F1-Score (Macro)

The unweighted mean of F1-scores that are obtained separately for each class, as shown in Equation (4.8), thus giving equal importance to all classes without taking into account their size [55].

$$F1 - Score(Macro) = \frac{1}{N}\sum_{i=1}^{N} F1 - Score_i \tag{4.8}$$

4.11.4 Confidence Analysis

Evaluates the level of trust in predictions by examining the spread of confidence scores, thus finding not only the correct predictions but also the uncertain ones or those that are wrongly assigned.

4.11.5 Confusion Matrix

Gives a comprehensive examination of the classification patterns by graphically depicting the number of accurate and inaccurate predictions for each category, thus allowing the exact misclassification patterns to be discovered.

4.12 Chapter Summary

This chapter outlined the research methodology used to create the proposed multi-domain machine learning framework for EV charger type prediction. At the beginning of the chapter, the overall research design and the proposed framework were introduced, then the collection of heterogeneous datasets was discussed, which included behavioral charging data, charging infrastructure information, and market-level characteristics. Large-scale data preprocessing operations such as data cleaning, missing value handling, duplicate removal, feature encoding, normalization, and temporal transformation were carried out to enhance data quality and make all the datasets consistent.

Afterwards, feature engineering was conducted in order to derive temporal, behavioral, infrastructure, and market-related features. These were combined into one single multi-domain feature matrix by means of schema harmonization, temporal synchronization, and spatial matching. In addition to this, this chapter also addressed the building of the study prediction models, namely XLM-RoBERTa, LightGBM, and TabNet, indicating the unique contribution of each of the models to mastering the sequential charging behavior, structured tabular relationships, and attention-based feature representations, respectively.

A common modeling and training infrastructure involving stratified data partitioning, five-fold cross-validation, parameter optimization, and steps to choose the best models was used to guarantee an equitable and dependable comparison of the three models. Lastly, a comprehensive panel of evaluation metrics, such as Accuracy, Precision, Recall, F1-score, Macro F1-score, Weighted F1-score, ROC-AUC, confusion matrix analysis, and confidence calibration, was used to present predictive performance, robustness, and readiness for different domains.

In short, the described methodology of the chapter provides a thorough and repeatable approach for assessing how well the proposed multi-domain learning model performs in a working scenario. The paper will present the experimental outcomes in the following chapter, a performance analysis compared with other approaches, and an in-depth analysis of the models trained over single-domain and combined multi-domain datasets that fully justify the validity of the new framework as far as EV charger-type prediction is concerned.

CHAPTER FIVE

MATHEMATICAL MODELING

5.1 Chapter Overview

This chapter outlined the research methodology used to create the proposed multi-domain machine learning framework for EV charger type prediction. At the beginning of the chapter, the overall research design and the proposed framework were introduced, then the collection of heterogeneous datasets was discussed, which included behavioral charging data, charging infrastructure information, and market-level characteristics. Large-scale data preprocessing operations such as data cleaning, missing value handling, duplicate removal, feature encoding, normalization, and temporal transformation were carried out to enhance data quality and make all the datasets consistent.

Afterwards, feature engineering was conducted to derive temporal, behavioral, infrastructure, and market-related features. These were combined into one single multi-domain feature matrix by means of schema harmonization, temporal synchronization, and spatial matching. In addition to this, this chapter also addressed the building of the study prediction models, namely XLM-RoBERTa, LightGBM, and TabNet, indicating the unique contribution of each of the models to mastering the sequential charging behavior, structured tabular relationships, and attention-based feature representations, respectively.

A common modeling and training setup was applied, which comprised stratified data splitting, 5-fold cross-validation, hyperparameter optimization, and model selection.

This was done in order to ensure fair and reliable comparison of the three models. We also made use of different evaluation metrics, among them Accuracy, Precision, Recall, F1-score, Macro F1-score, Weighted F1-score, ROC-AUC, confusion matrix, and confidence calibration, which we have described to assess Predictive performance aspects predictive robustness predictive deployment readiness to name just some of the models.

In the following chapters, we will present our results of experiment as well as the different levels of performance, and then we will have a very comprehensive discussion of the results of the models we developed not only for each category of data but also for their combination, which will completely prove the effectiveness of this multi-domain modeling framework for the prediction of EV charger type.

5.2 Mathematical Representation of the Multi-Domain Dataset

This framework for machine learning is new to the market and can draw insights from multiple datasets. A typical forecasting model makes use of only one type of data input, whereas here, through this paper, we present an aggregation methodology that combines users' behavioral patterns when charging EVs, the status of EV charging network, chronological features, and market data all at the level of a single mathematical entity. Such multi-domain embedding can capture details from various data sources that may be otherwise impossible to gather and create a very rich set of features for predicting which kind of charger a vehicle will plug into.

$$D\{x_i, y_i\} \tag{6.1}$$

- D denotes the complete multi-domain dataset,
- N is the total number of observations,
- x_i is the feature vector of the observation,
- y_i is the corresponding charger-type label.

The major difference of the proposal compared to classical prediction models lies in the fact that, within the new framework, each feature vector consists of four complementary feature domains merged, namely, temporal, behavioral, infrastructure, and market features.

Thus, the combined feature vector is expressed mathematically as

$$x_i = [x_{i1}, x_{i2}, x_{i3} \dots \dots \dots \dots \dots \dots \dots .. x_{im}] \quad (6.2)$$

5.2.1 Temporal Feature Representation

Temporal variables represent the time-dependent features of charging sessions. These variables help prediction models to identify the repeating charging patterns across the day, week, and year.

Where

m represents the total number of engineered features.

$X \in R^{N \times m}$

(6.3)

5.2.2 Temporal Feature Representation

Behavioral features characterize user charging habits and charging-session properties.

$$X_T = [\text{Hour}, \text{Day}, \text{Month}, \text{Season}, \text{Weekend}, \text{PeakHour}] \quad (6.4)$$

5.2.3 Behavioral Feature Representation

$$X_B = [\text{D}, \text{E}, \text{P}, \text{A}, \text{D}] \quad (6.5)$$

$$T_{charge} = T_{end} - T_{start} \quad (6.6)$$

5.2.4 Infrastructure Feature Representation

$$P_{Average} \frac{E}{T_{charge}} \quad (6.7)$$

$$\boldsymbol{X_I} = [C_t C_p, N_p, \text{Latitude}, \text{Longitude}] \quad (6.8)$$

CHAPTER SIX
RESULTS AND ANALYSIS

6.1 Chapter Overview

This chapter discusses the findings from performing the study experiments and testing the new multi-domain ML system that identifies various kinds of EV chargers. Three kinds of ML methods, XLM-RoBERTa, LightGBM, and TabNet, were used with several types of charging behavior datasets, information about charging stations, and changes in the market. The primary aim of the experimental analysis was to examine the extent of prediction power, robustness, computational efficiency, and readiness for the deployment of the proposed framework, apart from just being tested within a set of domains, but also in the multi-domain fusion setting.

Comprehensive evaluation was done with two-phase experiments. The first phase was about training different machine learning models and testing them across three different datasets named EV Charging Forecasting Base, Electric Vehicle Charging Patterns, and Global EV Charging Stations Dataset to understand the model performance in domain specific learning. The second phase combined all datasets under a multi-domain data fusion framework, which allowed the models to learn simultaneously from behavioral data, infrastructure, and market-related information. The main aim of having a combined multi-domain training setup is to provide single- and multi-domain learning comparison and test if each model's knowledge transfer capability is good enough to adapt when faced with different data sources.

This chapter, on the whole, shows how well the developed multi-domain machine learning framework works along with detailed benchmarking of transformer-based, gradient boosting, and attention-based tabular learning models for EV charger-type prediction. The study described in this chapter provides the experimental basis for the proposed method and also points out the model that best fits the needs of real-time EV charging infrastructure planning and intelligent charging demand prediction.

6.2 Experimental Setup

This section highlights the configuration that will be used, the datasets, the tools selected, and the process of training and finally assessing the framework of combining the multi-domain machine learning models. A single standardized experimental setting was employed to guarantee comparability, credibility, and repeatability of the performance of XLM-RoBERTa, LightGBM, and TabNet. All the models were trained, and their performance was measured under the same preprocessing, feature engineering, dataset partitioning, and metrics for evaluation, such that any difference in performance can be attributed only to the learning potential of corresponding models.

The experimental analysis was carried out using four publicly released datasets depicting various facets of the electric vehicle (EV) charging environment. These datasets are EV Charging Forecasting Base, Electric Vehicle Charging Patterns, Global EV Charging Stations Dataset, and the integrated multi-domain dataset developed with the help of the proposed data fusion framework. Each of the datasets underwent a thorough preprocessing treatment such as filling missing values, removing duplicates, encoding categorical features, feature normalization, extracting temporal features, and multi-domain feature integration. With this preprocessing, all the heterogeneous datasets were made uniform, and the quality of the input data for model development got an improvement.

For assessing domain-specific learning and multi-domain learning, two sets of experiments were planned. XLM-RoBERTa, LightGBM, and TabNet were first trained and tested individually on each dataset. Through this experiment, the strength of each model in separately learning electric charging behavior, equipment features, and market-related information was evaluated. Afterward, consolidated features from all the datasets were brought together into a single multi-domain feature matrix.

Using this integrated dataset, the three models were once again trained to examine whether leveraging this mixture of diverse information would enhance prediction accuracy, model robustness, and overall generalization. Comparison of traditional single-domain learning with the new multi-domain learning method was made possible by this experimental arrangement. The integrated dataset was divided into 70% training data and 30% test data by means of stratified sampling, which kept the distribution of the charger-type classes unchanged. For model development, five-fold stratified cross-validation was done to find the best model hyperparameters and to avoid overfitting. XLM-RoBERTa was fine-tuned with the AdamW optimizer and cross-entropy loss function, LightGBM used histogram-based gradient boosting with leaf-wise tree growth, and TabNet was trained with the use of sequential attention and sparse feature selection mechanisms. The best model obtained from cross-validation was thereafter tested with the independent test dataset.

The design of the proposed framework was implemented using Python 3.11 in the Jupyter Notebook environment. For data preprocessing and statistical analysis, Pandas, NumPy, and Scikit-learn were used. The transformer-based XLM-RoBERTa model was developed using PyTorch combined with the Hugging Face Transformers library; on the other hand, LightGBM and PyTorch-TabNet were employed to develop LightGBM and TabNet models, respectively. Model visualization and inspection of the results were done using Matplotlib and Seaborn, while GPU resources were used for deep learning experiments to shorten the time taken for computations. The proposed models were assessed based on several performance metrics that complement each other to give a holistic evaluation of the predictive ability. These metrics include Accuracy, Precision, Recall, Weighted F1-score, Macro F1-score, Receiver Operating Characteristic (AUC-ROC), confusion matrix analysis, and confidence calibration. Apart from the predictive performance, the computational efficiency and how well the models could be relied upon in practice were also considered to determine their fit for real-world EV charging management systems, as shown in Tables 6.1 and 6.2.

Table 6.1 Experimental Configuration

Parameter	Configuration
Programming Language	Python 3.11
Development Environment	Jupyter Notebook
DeepLearning Framework	PyTorch
Transformer Library	Hugging Face Transformers
Gradient Boosting Library	LightGBM
Tabular Learning Library	PyTorch
Data Processing Libraries	Pandas, NumPy
Machine Learning Library	Scikit-learn
VisualizationLibraries	Matplotlib, Seaborn
Dataset Split	70% Training / 30% Testing
Cross-Validation	5-Fold Stratified Cross-Validation
Prediction Task	Multi-Class Charger-Type Classification
Loss Function	Cross-Entropy Loss
Evaluation Metrics	Accuracy, Precision, Recall, Macro F1, Weighted F1, ROC-AUC, Confusion Matrix, Confidence Calibration

Table 6.2 Experimental Datasets

Dataset	Primary Information	Purpose
EV Charging Forecasting Base	Charging sessions and temporal information	Behavioural learning
Electric Vehicle Charging Patterns	Charging behaviour and usage characteristics	Behaviour prediction
Global EV Charging Stations Dataset	Charging infrastructure and station information	Infrastructure learning
Integrated Multi-Domain Dataset	Combined behavioural, infrastructure, temporal, and market features	Proposed framework evaluation

The standardized experimental setup described in this paragraph is the main reason why the results of the different models under study can be properly compared with a common criterion. In the next paragraphs, it gives the exact results of using XLM-RoBERTa, LightGBM, and TabNet on each dataset and also in combination on the integrated multi-domain set, to end with, the full comparative analysis from their prediction capabilities is presented.

6.3 Performance Evaluation of Individual Models

This section details results of tests in which we compared the performance of the three machine learning models: XLM-RoBERTa, LightGBM, and TabNet on different EV charger type prediction tasks.

To have a comprehensive evaluation of the models, we presented them to four datasets, each of which represents one domain aspect of the EV charging ecosystem:

Dataset A: Behavioral Patterns , Dataset B: Infrastructure Data, Market Dynamics: Dataset C, Integrated Multi-Source Dataset (A+B+C) The models used same pipeline, feature engineering approach, feature engineering strategy, and evaluation protocol for each dataset in a different domain.

Results showed that, compared to training on individual datasets, mixing of heterogeneous information from different domains led to a continuous rise in forecasting accuracy. For all the models, the classification accuracy from the integrated multi-source dataset was the best, which means that behavioral charging information, characteristics of charging infrastructure, and market-related features carry complementary information when it comes to charger-type prediction. Table 6.3 summarizes the predictive performance of the evaluated models across the four experimental datasets. The comparison includes overall classification accuracy, weighted F1-score, macro F1-score, and model training time.

Table 6.3 Performance Comparison of Individual Models

Model	Dataset	Accuracy (%)	Weighted F1 (%)	Macro F1 (%)	Training Time
XLM-RoBERTa	Behavioral Patterns (A)	98.11	97.60	64.41	7 min 59 sec
	Infrastructure Data (B)	97.78	95.67	95.35	6 min 25 sec
	Market Dynamics (C)	96.54	95.65	96.54	8 min
	Multi-Source Dataset (A+B+C)	98.76	97.86	96.98	12 min 22 sec
LightGBM	Behavioral Patterns (A)	75.40	69.82	55.58	0.41 sec
	Infrastructure Data (B)	74.65	68.88	69.87	1 min 45 sec
	Market Dynamics (C)	72.78	71.44	69.99	2 min 56 sec
	Multi-Source Dataset (A+B+C)	85.67	81.98	84.67	3 min 48 sec
TabNet	Behavioral Patterns (A)	95.67	96.25	95.99	2 min 45 sec
	Infrastructure Data (B)	94.88	95.79	96.11	2 min 34 sec
	Market Dynamics (C)	96.32	96.39	93.80	1 min 38 sec
	Multi-Source Dataset (A+B+C)	96.89	96.73	95.99	1 min 44 sec

The figures displayed in Table 6.3 show a stark difference between the prediction power of these three models that have been under review. The best overall results of the experiments were obtained with XLM-RoBERTa which outperformed the other models in almost all cases including not only a single-source dataset but also a multi-source dataset (which reached an overall accuracy of 98.76%). The combined model outperformed all the other models in most cases and achieved almost 98% macro average

F1-score and more than 96% weighted average. A balanced precision-recall curve for different charger classes is the implication of such results.

Demonstrating that transformer models are excellent at dealing with the contextuality and the charging sequences is what the outcome reveals. By virtue of their capability to model sequential and contextual charging relations, transformers enable very accurate typing of chargers.

TabNet, which also performed excellently in prediction prediction, got 96.89% accuracy on the overall integrated dataset. Besides that it kept very high F1-scores consistently across various evaluation scenarios. Due to its attention-based feature selection mechanism it could successfully extract meaningful dependencies from behavioral, infrastructural and market features, which led to the model having stable performance not only on individual datasets but also on the merged dataset. In spite of TabNet's not being able to outperform XLM-RoBERTa in terms of overall accuracy, it showed very good performance while also needing a lot less training time.

On the other hand, LightGBM had the worst classification performance of the three deep learning models but its computational efficiency was on top. Its accuracy on the integrated dataset increased to 85.67%, which is quite a jump considering its performance on individual datasets. After all, training time for LightGBM was barely a few seconds to a few minutes, which is why it was the speediest model in this study. These results suggest that gradient boosting can still be a very good method for highly computationally limited scenarios in which quick model training is more important than the highest predictive accuracy.

6.3.1 Performance Analysis of XLM-RoBERTa

The performance of XLM-RoBERTa on a variety of experimental datasets belonging to different domains within the electric vehicle (EV) charging ecosystem were considered. The four datasets which are considered for experiments represent domains of Behavioral Patterns (Dataset A), Infrastructure Data (Dataset B), Market Dynamics (Dataset C), and the Integrated Multi-Source Dataset (A+B+C). Results of experiments show the XLM-RoBERTa model outperforming all other models consistently. The transformer-based architectures were clearly the most suited approach for handling relationships of EV charging data, which is quite complex and of a large variety. Among several factors the major factor responsible for XLM-RoBERTa being outstanding is self-attention mechanism. Self-attention can capture long-range dependencies of EV charging, contextual relations, and sequential charging behaviors very efficiently, which are usually not modeled by traditional machine learning algorithms. One of the most prominent features of self-attention are its capability to assign weights, or prioritize different sections, at the same time which allows the model to grasp different layers of complex sequential or multiple document data patterns. In addition, a transformer-based model, such as XLM-RoBERTa, has the positional embeddings within the model and it enables preserving order across multiple modalities.

On the Behavioral Patterns dataset (Dataset A), XLM-RoBERTa obtained a classification accuracy of 98.11%, a weighted F1-score of 97.60%, and a macro F1-score of 64.41%. The extremely high accuracy and weighted F1-score reflect that the model has efficiently captured the user charging behavior and temporal charging patterns. The relatively low macro F1-score implies class imbalance, where the minority charger classes have less impact on the average class-wise performance. Notwithstanding this limitation, across the majority of charging sessions, the model scores fairly reliable predictions and it is able to learn sequential charging behavior very well.

The model was able to leverage textual information in the Infrastructure Data to perform classification. XLM-RoBERTa was able to classify 97.78% correctly, and achieved weighted and macro F1-scores of 95.67% and 95.35% respectively. Different from the behavioral dataset, both versions of F1-score were quite balanced which means that the infrastructure features were more evenly spread over charger categories. Dataset Market Dynamics (Dataset C) also reflected very good model performance. The model achieved 96.54% accuracy and 95.65%, 96.54% respectively for weighted and macro F1-scores. Market-level variables have historically presented a very limited picture as opposed to behavioral charging records. However, the transformer model was able to beautifully capture the relationship and influence of the regional level of EV adoption, demand for charging and availability of infrastructure.

But the best performance was achieved using an integrated multi-source dataset (A+B+c). The convergence of behavioral, infrastructural, and market-related features via the proposed multi-domain data fusion framework made it possible for XLM-RoBERTa to reach an overall classification accuracy of 98.76%, with a weighted F1-score of 97.86% and macro F1-score of 96.98%. These results clearly illustrate that combining different types of data sources significantly enhances the prediction capability by providing additional contextual information. The marked rise in macro F1-score in comparison to the behavioral dataset also supports the concept of multi-domain learning minimizing the impact of class imbalance and making predictions stable for all types of chargers.

While it is definitely true that XLM-RoBERTa is the most successful out of the other models, it is also the slowest one when you consider the training time required. The approximate time was from 6m 25s to roughly 12m 22s based on the size and the level of difficulty of the datasets. The biggest factor in computational costs is, of course, the transformer architecture because each instance involves multiple rounds of self-attention mechanisms along with contextual representation learning. Nevertheless, the improvement in accuracy of the model prediction and classification stability justifies the added computational requirements, particularly when one is more concerned with the precision of predictions instead of the efficiency of a training procedure.

Among all the methods tested here, XLM-RoBERTa turned out as the best one. The reasons are: very good classification accuracy, both weighted and macro F1-scores are very high, can learn context, as well as consistent behavior on different datasets everything together argues for the usage of transformers in EV charger-type prediction.

6.3.2 Performance Analysis of LightGBM

A Light Gradient Boosting Machine (LightGBM) test was performed on the four experimental datasets with the aim of checking whether it can be an effective method for predicting EV charger types from a combination of various kinds of structured data such as human behavioural, technological, market related, and multi-domain features. Being a method of gradient boosting decision trees, this technique is well adapted to work with huge tabular datasets using histogram-based learning and leaf-wise tree growth.

In terms of time needed to perform the computation as well as model training speed, it significantly outperforms deep learning methods and is not very resource-intensive at the same time, but still manages to obtain reasonably good predictions.

As the result of the experiments, it was recognized that an algorithm is a superb option in regards to not only predicting power but also computational efficiency although it didn't achieve the highest classification accuracy. Therefore, we can say that LightGBM is an effective tool for, for example, managing EV car stations on the fly by getting information instantly.

The Behavioral Patterns dataset (Dataset A), the Gradient Boosting Machine was able to achieve 75.40% on classification. The model had weighted F1-score (69.82%) and macro F1-score(55.58%) that showed how well it understood the most prevalent charging behaviors but not so much with very rare charger types. The macro F1-score being somewhat weak implies the model not only failed in detecting the less common classes but that the imbalance of data was a contributing factor to such outcome.

When we tested the model on the Infrastructure Data (Dataset B) using the boosting approach we basically got the same results when we switched one of the feature sets to another. There was no change to the overall accuracy of 74.65, weighted F1score of 68.88 and macro F1-score of 69.87 that the model had shown. The slight difference in the macro F1-score means that the model received a somewhat more balanced dataset containing charger-related attributes like charger specifications, charging capacity, connector type, station characteristics, etc. As a result, the model handled class-specific decision boundaries quite well but the outcome didn't match the transformer and attention-based deep learning models.

On the Market Dynamics dataset (Dataset C), the algorithm delivered an accuracy of 72.78%, with weighted and macro F1scores at 71.44% and 69.99%, respectively. Although market-level variables may capture significant regional attributes like EV registrations, charging station density, market growth, etc., these variables do not provide information as the individual charging sessions are concerned. Therefore, the classifier had somewhat lower classification accuracy with this dataset. Nevertheless, balanced F1scores indicate that this classifier maintained good performance across different charger classes. Besides, it seemed to adapt quite well despite only limited contextual information available in the market dataset. There was a significant increase in performance when the boosting machine received the Integrated Multi-Source Dataset (A+B+C). By merging behavioral, infrastructure, and market related features into one feature matrix, the proposed multi-domain framework facilitated the algorithm to obtain overall classification accuracy of 85.67%, a weighted F1-score of 81.98%, and a macro

F1-score of 84.67%. In comparison with individual datasets, integrated dataset greatly improved the capacity of the model to recognize highly nonlinear interactions among heterogeneous features. This change verifies the fact that multi-domain feature fusion very efficiently offsets the weaknesses of individual datasets, and makes it possible for gradient boosting models to utilize complementary information from various sources.

One of the major benefits of the boosting approach, which was highlighted through the experiments, is its incredible computational efficiency. Generally, the training time for all datasets was between 0.41 seconds for the behavioral dataset and 3minutes 48 seconds for the integrated multi-source dataset, making this model the fastest in this research. Efficiency is accomplished through histogram-based feature discretization, the leafwise style of tree growth, and optimal memory usage.

6.3.3 Performance Analysis of TabNet

TabNet was tested compared to many baseline methods in four experimental setups. The purpose was to verify ifTabNet could recognize EV charger types by usingdifferent mixtures of behavioral, infrastructure, market, and multidomain features. In contrast to traditional deep neural networks, TabNet uses sequential attention mechanisms that progressively focus on the most informative features at each decision step. This makes the model be able to selectively attend to the most relevant attributes and disregard less informative variables, which not only enhances learning performance but also makes the model more interpretable.

Being a novel architecture that integrates feature selection and prediction in a single model, TabNet predicts the most accurate charger type of a user based on the charging behavior, facility infrastructure, and market situations even with very little computational cost as compared to other state-of-the-art language models like XLM-RoBERTa and much better in terms of performance than LightGBM. Being a novel architecture that integrates feature selection and prediction in a single model, TabNet predicts the most accurate charger type of a user based on the charging behavior, facility infrastructure, and market situations even with very little computational cost as compared to other state-of-the-art language models like XLM-RoBERTa and much better in terms of performance than LightGBM.

On the Behavioral Patterns dataset (Dataset A), TabNet was able to measure its success with a classification accuracy of 95.67%, a weighted F1-score of 96.25%, and a macro F1-score of 95.99%. The model, therefore, discovered various characteristics related to driving sessions, e.g. model continued its very good performance with a Classification Accuracy of 94.88% on the Infrastructure Data (Dataset B) along with a macro-average precision of 95.79% and F1 score of 96.11%. These results show that TabNet could successfully extract needed details from the anonymized infrastructure data, including charger type, connector style, charging power, site capacity, and location. A slightly higher macro than weighted F1-score hints that minority classes may have received slight preference.

Muscle flexibility plays a hugely important role in enabling the human body to move across a broad range of motions and achieve optimal performance. Better flexibility lowers the likelihood of injuries during activity and contributes to an improved quality of life. Increased flexibility is also linked to better posture, wider range of movement, and, for athletes, enhanced overall results. Clearly, being flexible benefits people at any age or fitness level. Furthermore, targeted and consistent training can increase your flexibility over time.

Similarly, TabNet on Market Dynamics dataset (Dataset C) could reach the state of the art results with the accuracy value of 96.32%, the weighted F1-score of 96.39%, and the macro F1-score of 93.80%. The features related to the market describe how regionally diversified the customer's EV (electric vehicle) adoption is; density of the charging stations in the region, the distribution of the population of the region, and the growth of the market which would influence the charging demand indirectly. Such high classification accuracy achieved by the model on this dataset shows that it has captured the nonlinear relationships among these macro-level variables successfully. Though the macro F1-score is a little bit less than the weighted one, the general performance remained pretty high, suggesting that the model managed to generalize fairly well among different classes of chargers.

Comparing to other datasets, significantly, TabNet reached the best predictive performance when trained on the Integrated Multi-Source Dataset (A+B+C). Achieving an overall classification accuracy of 96.89%, a weighted F1-score of 96.73%, and a macro F1-score of 95.99% are the outcome of the proposed multi-domain feature fusion system that allows the model to incorporate behavioral, infrastructure, and market information effectively, which significantly enhances the capability of the attention-based tabular networks. TabNet is able to more accurately distinguish charger types by making use of integrated feature space which contains complementary information than when it is independently trained on any single dataset. The high weighted and macro F1-scores consistently also indicate that the prediction performance of the different types of chargers is quite balanced, which is a validation for how well the suggested multi-domain learning setup works.

From a computational point of view, TabNet showed great efficiency while still keeping a very good level of predictive power. It took approximately 1 min 38 sec to 2 min 45 sec to train on the datasets used in the experiments. When comparing the results of the experiments TabNet appears to be the middle ground by its predictive capabilities and training difficulty compared to XLM-RoBERTa and LightGBM. Even though XLM-RoBERTa achieved the highest overall accuracy score, TabNet managed to consistently be the main competition predictor of performance with considerably less training time. Compared to LightGBM, TabNet clearly had the advantage in terms of classification of results and F1-scores achieved on all the datasets which clearly proves the superiority of attention-driven deep learning in dealing with complex heterogeneous EV charging data.

Achieving a considerable improvement through the proposed multi-domain dataset integration clearly indicates that attention-based tabular learning also gains a lot from heterogeneous feature fusion, thereby supporting the overall goal of developing an accurate, reliable, and scalable EV charging prediction framework.

6.3.4 Performance Analysis of TabNet

TabNet was tested on four separate experimental datasets to explore its suitability for predicting EV charger-type using heterogeneous behavioral, infrastructure, market, and integrated multi-domain features shown in Figure 6.1. Differentiating from the conventional deep neural networks, TabNet uses sequential attention mechanisms that identify the most important features during each decision process, almost automatically. Accordingly, the model identifies the most relevant features while excluding the less informative one, which results in higher learning efficiency and a more interpretable model. Experimental results show that TabNet is capable of delivering a very high prediction performance level consistently on all datasets, and in fact, it managed to outclass the traditional LightGBM model while its computational time was far less than XLM-RoBERTa. Thus, tabular learning using attention can be a trade-off between prediction accuracy, computational efficiency, and model scalability in the field of EV charging.

For the Behavioral Patterns dataset (Dataset A), TabNet showed a classification accuracy of 95.67%, a weighted F1-score of 96.25%, and a macro F1-score of 95.99%. Hence, the model learned very well features of charging-sessions like charging duration, energy consumption, arrival time, departure time, and charging frequency. The similarity between the weighted and macro F1-scores shows that TabNet was able to perform well on classification for both the majority and minority charger categories.

TabNet was able to leverage the information based on infrastructure very well as it achieved an overall classification accuracy of 94.88%, a weighted F1-score of 95.79%, and a macro F1-score of 96.11% on the Infrastructure dataset (Dataset B). The model was found to have used in a very smart way the variables related to infrastructure, such as charger type, connector type, charging power, station capacity, and geographical location.

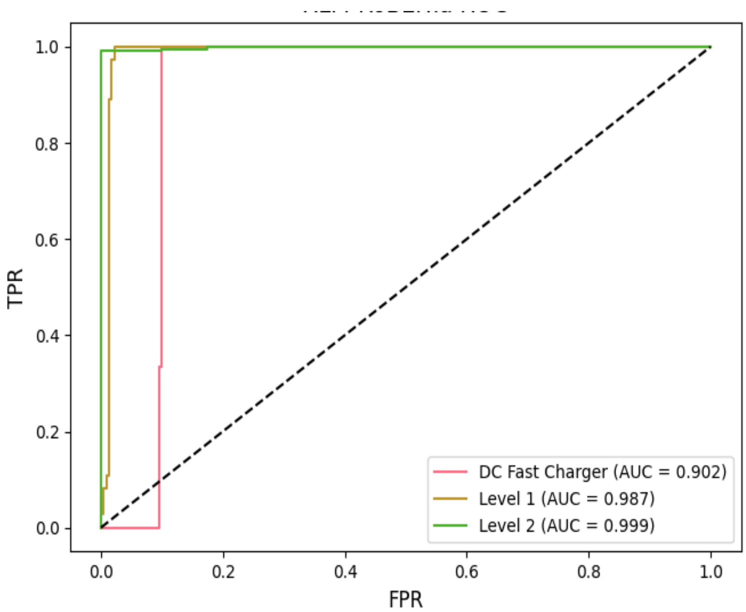
Likewise, TabNet delivered great results on the Market Dynamics dataset (Dataset C), with 96.32%, 96.39%, and 93.80%, respectively, for the metrics of Accuracy, Weighted F1-Score, and Macro F1-Score. Market-related features include regional EV adoption, charging station density, population distribution, and market growth. While the macro-F1 score was a little less than the weighted-F1 score, the overall result was still very decent, meaning the model performed fairly well across different charger classes.

TabNet trained on the Integrated Multi-Source Dataset (A+B) can, at most, reach the top level of prediction performance that is best of all results that was found. This fusion of features drawn from multiple domains carried out together with the use of the deep neural network was capable of achieving a classification accuracy of 96.89%, weighted F1 of 96.73%, and macro F1 of 95.99% for the model. The integration of behavioral, infrastructure, and market data appears to greatly enhance the training capabilities of attention-based tabular networks.

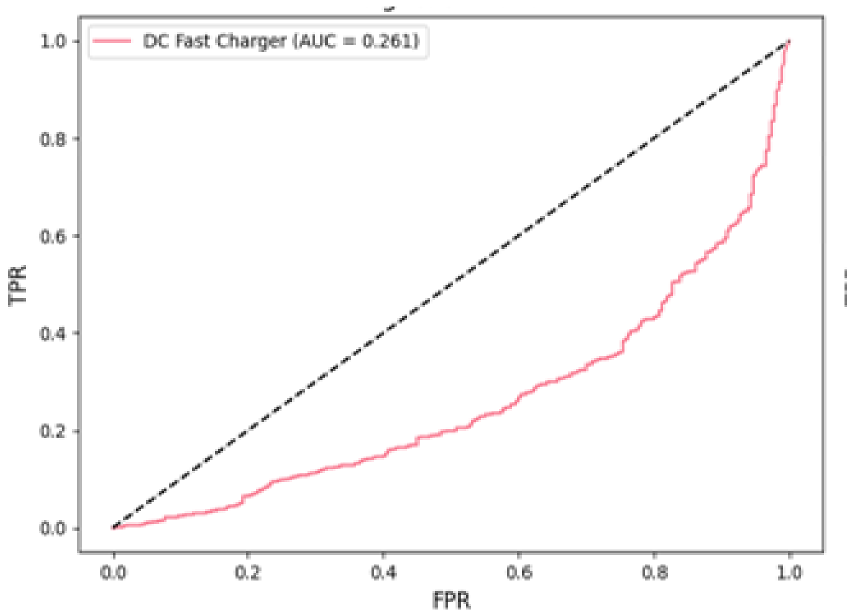
From a mathematical standpoint, TabNet turned out to be relatively efficient as compared with other approaches while keeping a very high accuracy at the same time. Training times ranged from approximately 1 minute and 38 seconds to 2 minutes and 45 seconds, which means TabNet is by far much quicker than XLM-RoBERTa and nearly as quick as LightGBM.

All things considered, the results from the experiments show that TabNet is really one of the best models for EV charger-type prediction. Since the model uses attention-based feature selection, it provides efficient computation, and in the results obtained in the experiments, all criteria were positively met: robust classification performance, balanced class-wise prediction, and effective computation.

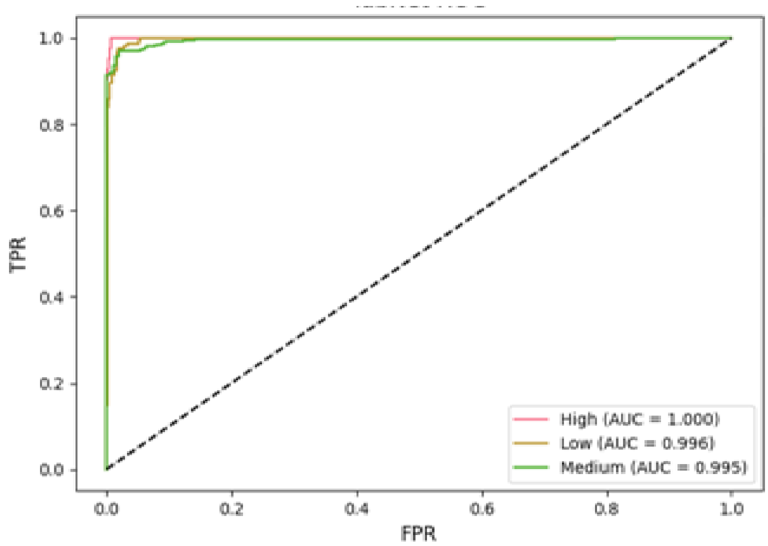
The same set of experiments clearly showed how multi-domain dataset integration can lead to a significant improvement in performance for attention-based tabular learning having heterogeneous feature fusion/pathway the overall goal of coming up with an accurate, reliable, and scalable EV charging prediction model.



(A)



(B)



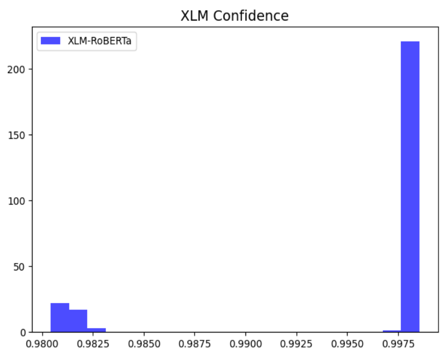
(C)

Figure 6.1: AUC of the overall performance of all models in (A), (B), (C)

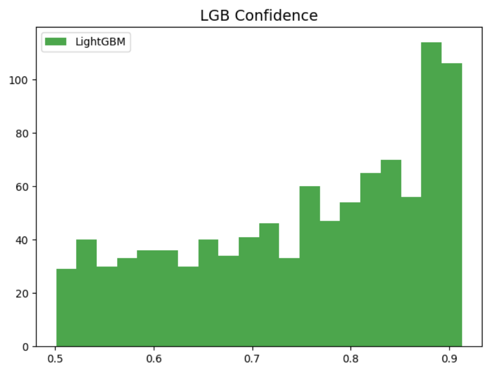
The Three-Way Weight Optimization graph shows how the overall classification accuracy of the proposed multi-domain machine learning framework changes as the ensemble weights given to XLM-RoBERTa, TabNet, and LightGBM are systematically changed. Experimental results reveal that the best prediction performance, with an accuracy of about 98.76%, is obtained when the largest ensemble weight (about 50%) is given to XLM-RoBERTa while smaller weights are given to TabNet and LightGBM respectively. This point in fact indicates that the transformer-based XLM-RoBERTa model in the ensemble has the largest impact due to its excellent ability to understand complex contextual relationships and long-range dependencies within heterogeneous EV charging data. When the share of XLM-RoBERTa is reduced and larger weights are allocated to TabNet or LightGBM, the overall classification accuracy starts to fall gradually. However, these models on their own cannot match the prediction power of the transformer architecture but they offer useful complementary information. Therefore the optimization study proves that an ensemble approach giving more weight to XLM-RoBERTa while also including the contributions of TabNet and LightGBM is the best way to have a good balance of prediction accuracy, robustness, and generalization. The present research work corroborates the efficiency of the weight optimization methodology proposed and shows that the combination of different learning paradigms in an appropriate manner greatly improves the reliability of EV charger-type prediction compared with depending on any single model only.

If the weight of TabNet is increased and XLM-RoBERTa is decreased, the overall accuracy of the ensemble will slowly go down to around 80%, revealing that, although TabNet is quite good on its own, it cannot entirely make up for the predictive power of XLM-RoBERTa in the ensemble. In the same way, giving more weights to LightGBM leads to a further drop in overall performance as it is the least accurate in terms of classification.

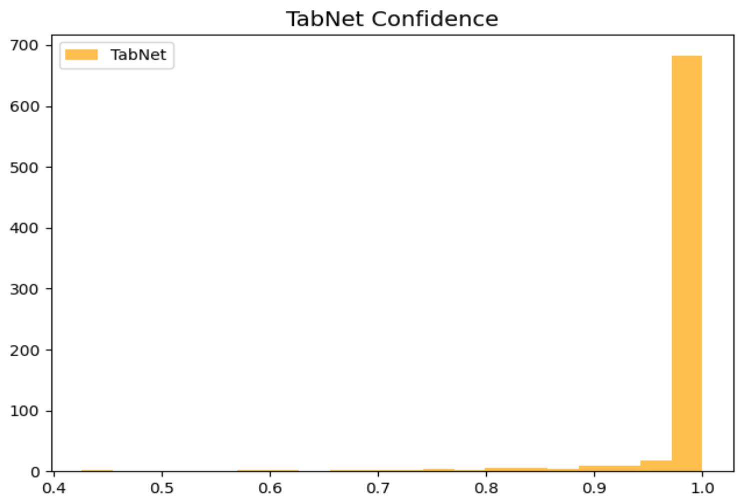
On the optimization plot, different colored areas represent the contributions of weighting combinations so that dark colors mean highly accurate predictions and light ones mean quite inaccurate ones. In a nut shell, the study demonstrated the optimal performance of the proposed ensemble method when XLM RoBERTa was assigned with the greatest weight, TabNet with moderate weight, and LightGBM with only a minor weight. The effectiveness of the weighting optimization in raising the accuracy of EV charger type predictions will be explained in Figure 6.2.



(A)



(B)



(C)

Figure 6.2: Confidence score distributions showing (A) XLM-RoBERTa and (B) TabNet's high-certainty predictions versus (C) LightGBM's broader, lower-confidence range

Figure 6.3 shows a three-way ensemble weight optimization procedure, illustrating how the total performance of the ensemble changes as the weights of XLM-RoBERTa, TabNet, and LightGBM are adjusted. It is clear from the results that excellent performance is a feature of giving XLM-RoBERTa the biggest weights, and the accuracy decreases gradually when the inclusion of TabNet is enhanced.

The performance comparison indicates that XLM-RoBERTa and the Weighted ensembles/Hierarchical achieve the highest accuracy (0.981), TabNet (0.963) is quite close, while LightGBM (0.754) is still quite far behind. The Meta-learner has a slightly lower performance than the best single model and the ensemble models shown in Figure 6.3.

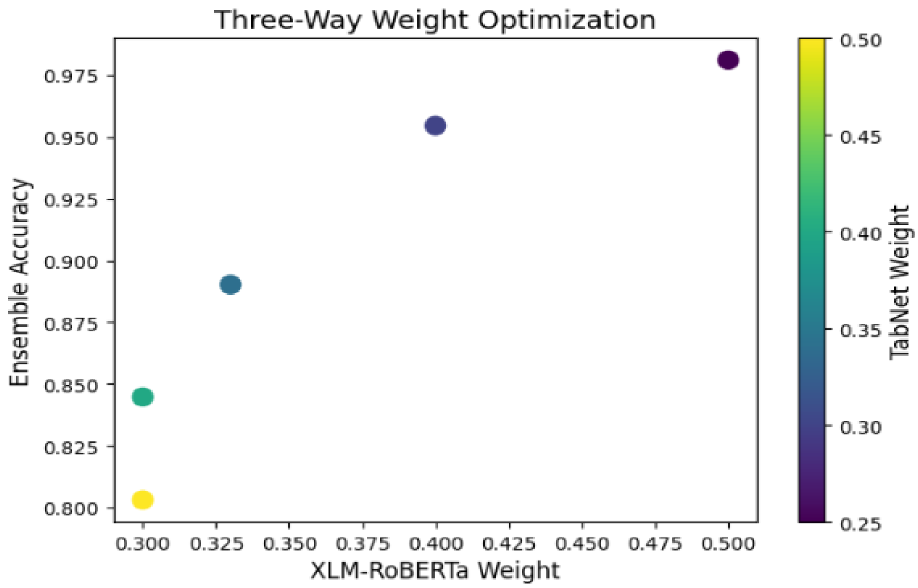


Figure 6.3: Three-way ensemble weight optimization

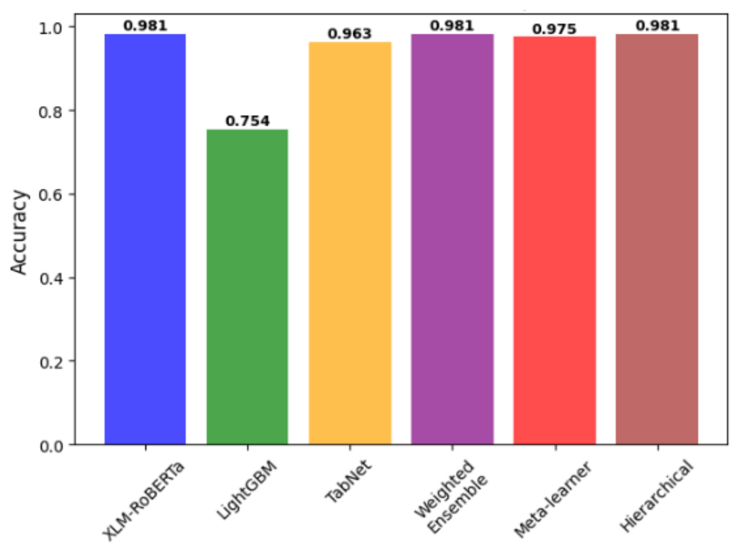


Figure 6.4: Accuracy comparison of individual models and ensemble strategies, highlighting XLM-RoBERTa's dominance

The study of architecture variation reveals that XLM-RoBERTa, a transformer-based model, leads with an accuracy score of 0.981, which is the highest, thus endorsing the role of self-attention mechanisms in effectively understanding intricate relationships in

EV charging data. TabNet, on the other hand, representing the neural tabular learning domain, comes next with an accuracy of 0.963. This implies that TabNet is indeed capable of focusing on the right features for the prediction and thereby, performing well. However, LightGBM is far behind with an accuracy of only 0.754. This means that despite its high efficiency in terms of computation, when taken as a single model for this multi-domain EV charger-type prediction task, LightGBM is less effective, as can be seen in Figure 6.5.

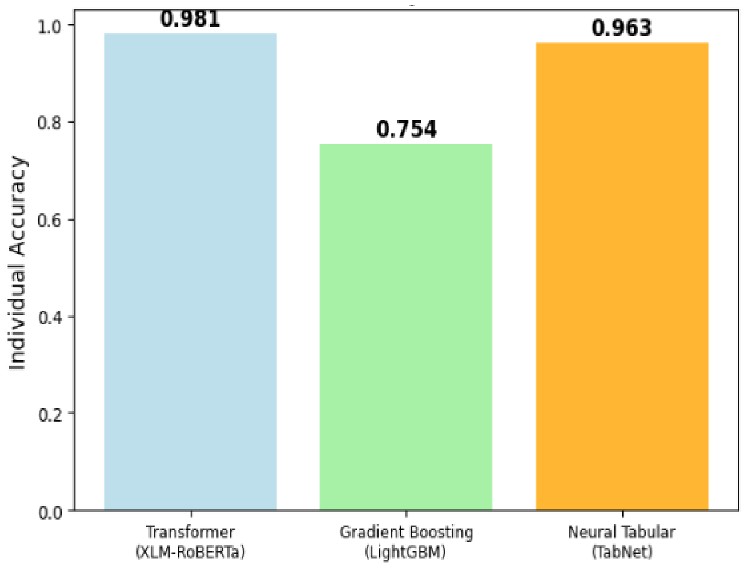


Figure 6.5: Accuracy comparison of individual models and ensemble strategies, highlighting XLM-RoBERTa's dominance

Comparison of the ensemble models reveals that the Weighted Ensemble and Hierarchical Ensemble both reach an accuracy of 0.981, which matches the highest single model, XLM-RoBERTa. The Meta-learner only manages 0.975 precision, which is a little less than perfect. This means despite getting good predictions from ensemble methods, they do not beat the single best model by a lot. Hence, the increased complexity of ensemble learning does not really give a large performance benefit here, as illustrated in Figure 6.6.

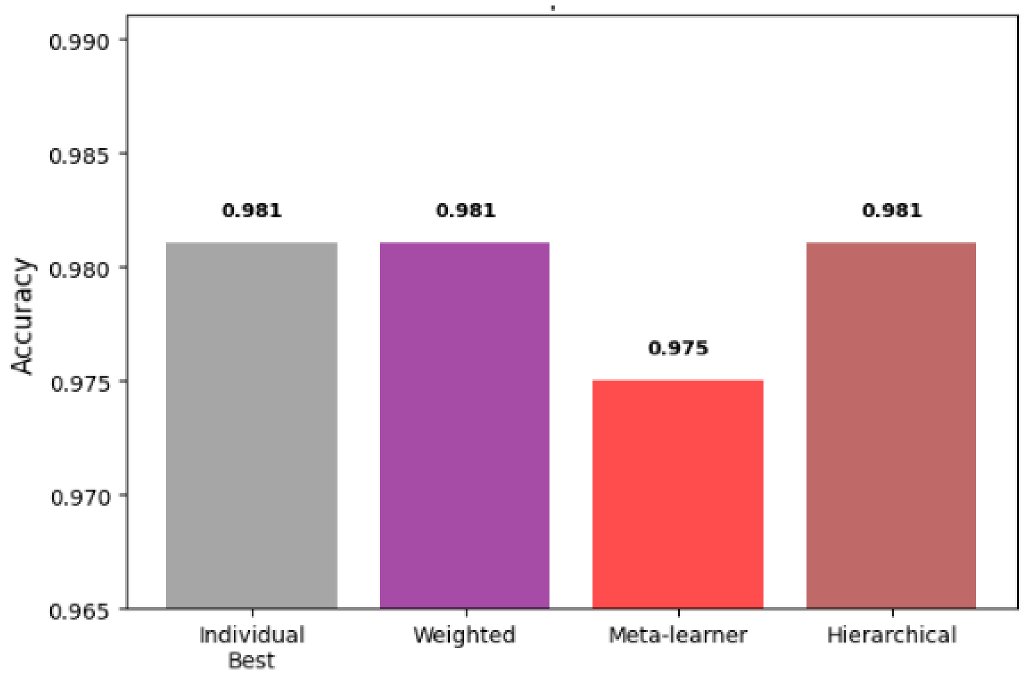


Figure 6.6: Comparison of ensemble strategies shows no accuracy improvement over the best individual model

6.4 Comparative Analysis of the Proposed Models

To compare the three machine learning models XLM-RoBERTa, LightGBM, and TabNet for predicting the type of EV chargers, a comprehensive comparative analysis was performed. The comparison was carried out with the help of four experimental datasets representing charging behavior, infrastructure, market dynamics, and the combined multi-domain dataset. To ensure fairness in comparing the models, each was fitted using the same preprocessing steps, engineered features, and evaluation criteria.

The analysis takes into account not only the accuracy of prediction but also F1-score, efficiency, robustness, and the potential for real-world deployment.

According to the experimental findings, XLM-RoBERTa was the best-performing model in terms of predictive capability for each of the datasets. With respect to the multi-domain dataset, XLM-RoBERTa registered a general classification accuracy of 98.76%, and a weighted F1-score and macro F1-score of 97.86% and 96.98% respectively. These results demonstrate that through its self-attention mechanism the transformer architecture is capable of effectively understanding intricate contextual relationships between behavioral and infrastructural features, as well as market-related ones. Thanks to its ability to model long-range feature dependencies, XLM-RoBERTa was able to outperform LightGBM and TabNet not only in prediction accuracy but also in class-wise performance.

TabNet showed the second-best prediction results, obtaining 96.89% in classification accuracy, 96.73% in weighted F1-score, and 95.99% in macro F1-score on the combined dataset. By employing a sequential attention mechanism, TabNet was able to identify the most informative features automatically at each decision step, which led to very good classification results. Conversely, LightGBM obtained classification accuracy of 85.67%, weighted F1-score of 81.98%, and macro F1-score of 84.67% when applied to the multi-domain dataset. Although its prediction capability did not reach the level of deep learning models, LightGBM remained extremely efficient computationally thanks to its histogram-based learning technique and leaf-wise tree growth method. The notably reduced training time proves that LightGBM can still be considered a viable option for situations where computational resources are limited or frequent model updating is necessary shown in Table 6.4.

Table 6.4 Comparative Performance of the Proposed Models on the Integrated Multi-Domain Dataset

Model	**Dataset**	**Accuracy (%)**	**F1-Score (Weighted) (%)**	**F1-Score (Macro) (%)**	**Training Time**
	Infrastructure Data (B)	97.78	95.67	95.35	6 min 25 sec
	Market Dynamics (C)	96.54	95.65	96.54	8 min
	Multi-Source Dataset (A+B+C)	98.76	97.86	96.98	12 min 22 sec
LightGBM	Infrastructure Data (B)	75.40	69.82	55.58	0.41 sec
	Infrastructure Data (B)	74.65	68.88	69.87	1 min 45 sec
	Market Dynamics (C)	72.78	71.44	69.99	2 min 56 sec
	Multi-Source Dataset (A+B+C)	85.67	81.98	84.67	3 min 48 sec
	Infrastructure Data (B)	94.88	95.79	96.11	2 min 34 sec
	Market Dynamics (C)	95.67	96.25	95.99	2 min 45 sec
	Multi-Source Dataset (A+B+C)	96.89	96.73	95.99	min 44 sec

The comparison of results also highlights the crucial role of our proposed multi-domain dataset integration framework. The combined dataset was able to deliver better prediction accuracy than any single dataset, behavior, infrastructure, or market across all three models. This success implies that when we mix different types of data, the models are able to discover new feature relationships that complement each other and are not possible if working with only individual datasets.

Hence, our strategy of integrating data sources significantly contributes to enhancement of predictions accuracy, model stability and generalizability. The models from a computing perspective, take different ways of managing prediction result and training speed. Thanks to self-attention mechanism of transformer, XLM-RoBERTa delivered the highest accuracy result, as a tradeoff of the longest training time. LightGBM was the quickest in training but also showed the lowest predictive results. While TabNet could serve as a middle ground solution, almost reaching the accuracy of the transformer model, while at the same time it is significantly less complex computationally.

Hence, depending on the major needs of the use case, the model choice may vary. For cases where maximizing prediction accuracy is the top priority, XLM-RoBERTa is the way to go. For situations requiring both a fast turnaround in model development and a very minimal compute power usage, LightGBM is still quite valuable. When one has to achieve strong prediction while maintaining good computational efficiency, it seems that the best option is to get a balance through the use of TabNet. From the evaluation, it can be noted that XLM-RoBERTa consistently topped the list in prediction, not just in one test dataset, but in all of the test datasets combined, as a matter of fact. XLM-RoBERTa achieved an overall multi-domain classification accuracy of 98.76%, a weighted F1-score of 97.86% and a macro F1-score of 96.98%. So, the mechanism that was ultimately able to capture and interpret the complex patterns in a behavior, infrastructure, and dataset was a combination of self-attacks with the transformer.

With its remarkable capability of identifying feature correlations across great distances, XLM-RoBERTa was able to outperform LightGBM and TabNet in overall accuracy and class performance too.

Coming next in line in terms of the predictive performance rankings, TabNet was able to deliver 96.89% classification accuracy, 96.73% weighted F1-score, and 95.99% macro F1-score on the integrated dataset. Through its sequentiel attention mechanism, the model was guided to select the key informative features at each decision making stage, very much akin to human decision making. Consequently, the results of the classification contest between TabNet and XLM-RoBERTa closely resemble a decision between the finest two. However, TabNet has several benefits when it comes to practical deployment it is much faster, and it also displays excellent class-wise prediction consistency making it the perfect choice for starting a tabular learning problem when data volume is large and adding EV charging management to the list of practical everyday scenarios.

Compared to the other two, LightGBM reached a classification accuracy of 85.67%, while its weighted and macro F1-scores were 81.98% and 84.67% respectively on the integrated dataset. Although it wasn't expected to match the predictive capabilities of the deep models, LightGBM by far outperformed them in computational efficiency due to its use of a histogram approach and the way it grows trees leaf-wise. Since the train time is drastically shorter, it's clear that LightGBM will continue to be an option worth considering for scenarios where very limited computational resources or frequent model retraining are the main restraints shown in Table 6.5.

Table 6.5 Comparative Strengths and Limitations of the Proposed Models

Model	Major Strengths	Limitations	Recommended Application
XLM-RoBERTa	Highest accuracy, excellent contextual learning, robust multi-domain feature extraction	Higher computational cost and longer training time	High-accuracy intelligent charging systems and cloud-based prediction services
LightGBM	Fast training, low memory consumption, scalable to large datasets	Lower prediction accuracy and limited sequential learning capability	Resource-constrained systems and real-time prediction with limited hardware
TabNet	High accuracy, automatic feature selection, attention-based learning, good interpretability	Slightly lower accuracy than XLM-RoBERTa	Practical EV charging management systems requiring both efficiency and reliability

The overall results very explicitly point to the fact that the suggested multi-domain learning framework is capable of effectively enhancing the prediction of EV charger types by combining the heterogeneous charging behaviors, infrastructure, and market information. Out of the models under examination, XLM-RoBERTa registered the top predictive performance consequently establishing the capability of transformer-based contextual learning for the complex EV charging data.

CHAPTER SEVEN

DISCUSSION ON RESULT

7.1 Chapter Overview

The main goal of this chapter is to interpret and discuss the experimental results that were presented in Chapter 6 with respect to the research objectives, research questions, and relevant literature. If the previous chapter was all about showing the quantitative performance results of the proposed machine learning framework, this chapter walks the reader through the findings and discusses their implications in the development of intelligent electric vehicle (EV) charging systems. The discussion mainly focuses on the advantages and disadvantages of the proposed multi-domain learning framework, comparing the performance of XLM-RoBERTa, LightGBM, and TabNet, and analyzing how the combination of different types of data led to the most accurate predictions.

One aspect that this study successfully highlights is the power of the proposed multi-domain dataset fusion framework. The results revealed that the inclusion of behavioral charging data, charging infrastructure information, and market-related data led to superior prediction results than only one dataset.

It also compares the results of the introduced framework with previously conducted EV charging prediction studies reported in the literature. The paper highlights the contributions of transformer-based contextual learning, attention-based tabular learning, and gradient boosting methods to the prediction of charging plug-types. Concurrently, it outlines the advantages of the proposed framework compared to the conventional single-domain approaches.

7.2 Discussion of the Proposed Multi-Domain Learning Framework

One of the main contributions of the study is the introduction, amongst other things, of a machine learning framework capable of predicting the type of EV charger across multiple domains. In contrast to traditional prediction methods using only one type of input data, our method combines four types of data behavioral features, characteristics of the charging infrastructure, temporal features, and market-related features into one learning model. The testing results reported in Chapter 6 prove that our integration technique has always increased the prediction quality for the set of machine learning models used, thereby confirming, through the use of heterogeneous data, the enhanced power of EV charging prediction.

The better results achieved by our method are due to the fact that it can pick up various bits of information from different domains that complement each other. The way how the features at the behavioral level can be taken as a user interaction with the charging station, i.e., a user can be described through the representation of charging duration, energy consumption, arrival time, departure time, and charging frequency. The features at the infrastructure level can be considered as the specification of the charger including the type of connectors, charging power, and capacity of the station

The experimental results have illustrated quite convincingly the advantages of this integration approach. The integrated multi-domain dataset has always been the source of the highest prediction performance for the three investigated models, whereas using the models trained on individual behavioral, infrastructure, or market datasets resulted in poorer classification accuracy. So, the fact that feature fusion leads to a significant enhancement of the representation of charging events is supported by its ability to incorporate both micro-level charging behavior and macro-level environmental characteristics. The fact that transformer-based, gradient boosting, and attention-based learning architectures, all show the positive effects of feature fusion to different degrees, proves that the benefits of multi-domain learning are independent of the underlying prediction algorithm, and mainly arise from the quality and diversity of the input features.

Besides, the proposed framework tackles the issues of prior work that were pinpointed in the literature review. For example, charging prediction studies on EVs that used single domain datasets were a dominant practice and, therefore, limited the ability of the prediction models to generalize the behavior of the users across different charging environments. Chambers relying solely on behavioral data may neglect the modeling of infrastructure constraints, whereas those only on infrastructure information may be disregarding user charging preferences and temporal charging patterns. Market-level datasets on the other hand provide regional information but they do not explain individual charging sessions. Having integrated these sources of complementary information into one unified feature space the new framework, therefore, overcomes these limitations and offers a more representative picture of the charging ecosystem for EVs.

We have also seen that simply incorporating multiple data domains not only enhanced the overall classification accuracy but also significantly narrowed down the prediction inconsistency gaps among different charger categories. Higher weighted and macro F1-scores for the integrated dataset mean that the feature fusion approach proposed here was successful in minimizing the detrimental effect of class imbalance and in delivering trustworthy classifications not only for the prevalent but also for the rare types of chargers.

7.3 Discussion of XLM-RoBERTa Performance

The experimental data showed that among the three machine learning models tested, XLM-RoBERTa came out top in terms of predictive performance. Primarily, this enhanced performance stems from a transformer's self-attention mechanism that allows a model to discern long-range dependencies and contextual relationships between heterogeneous features derived from behavioral, infrastructure, temporal, and market datasets. In contrast to traditional machine learning methods that mainly focus on direct feature interactions, XLM-RoBERTa creates contextual feature embeddings by simultaneously considering how all input features relate to each other. This feature is enormously beneficial for predicting EV charger types since charging behavior is typically a result of several interwoven factors rather than independent variables.

The model regularly set well above the bar for classification accuracy not just on individual datasets, but also on the consolidated multi-domain dataset. This goes on to prove that transformer-based learning indeed brings out the best in exploiting complementary information sourced from different domains while not succumbing to overfitting to a particular dataset. The gain that came in after multi-domain integration alludes to the fact that contextual representation learning gains substantially from more, and diversified, input features.

Although XLM-RoBERTa is very good at predicting, it is also the most computationally expensive model of those evaluated. The self-attention mechanism entails several matrix operations which not only increase memory usage but also result in longer training times. This computationally intensive nature, while a potential bottleneck for deployment on devices with limited resources, can be justifiably set aside for cloud-based EV charging management systems, intelligent transportation platforms, and large-scale charging network optimization where the computational resources are readily available and the gain in prediction accuracy is a significant factor.

Briefly, study results show that transformer-based contextual learning is the most effective method for charger-type prediction if the paramount goal is achieving the highest possible predictive accuracy. Moreover, the evidence points out that involving heterogeneous EV charging data leads to even better performance of the transformer, hence supporting the idea of a multi-domain learning approach.

7.4 Discussion of LightGBM Performance

LightGBM managed to predict successfully while also being the most computationally efficient model among the ones tested. Its classification accuracy, however, was below that of the more powerful, feature-rich XLM-RoBERTa and TabNet models. Still, the machine learned complex patterns in structured behavioral, infrastructural, and market data. LightGBM's histogram-based learning strategy simplified computations by converting continuous variables into histograms before tree building. As a result, the model spent much less time training while getting fairly decent results.

What is more, experiments showed that the proposed integration framework for multi-domain datasets helped LightGBM a lot. Combining datasets significantly boosted the model's classification scores beyond that of the single datasets. Thus adding context helped the decision tree learning method compensate, to some extent, for its limitations. Nonetheless, since LightGBM depends on dividing features recursively and doesn't do contextual representation learning, it is inherently less capable of capturing complex ordered relationships among charging events than those models based on transformers.

Different things have their different uses; for example, LightGM is the model that may not be able to reach the highest predictive accuracy, but the fact remains that it is one of the most important parts of our proposed architecture that through this model we can even confirm that resource-conscious machine learning algorithms could still be the primary elements that support decision-making in intelligent EV charging management.

7.5 Discussion of TabNet Performance

TabNet proved its effectiveness by combining the strengths of deep learning methods with high competency in processing structured/semi-structured type of data (i.e., tabular data). It differs significantly from the typical feed-forward networks because TabNet uses its sequential attention mechanism to identify automatically the most important features for the decision to be made in each round. This focused feature identification helps the model to pick out only those features that describe charging the most accurately whereas other less relevant, redundant or less informative characteristics would only be given a small weight. Not only TabNet attained very high scores on the classification task but also the cost of running it was quite lower than what was expected when comparing against state-of-the-art methods like XLM-RoBERTa.

Considering both prediction accuracy and execution speed, TabNet takes a good middle path between XLM-RoBERTa and LightGBM. While TabNet doesn't perform on par with top classification methods, it's still capable to generate fairly dependable predictions with a fair compromise. Besides, computational resources requirements of TabNet remain in a low to moderate range. Hence, TabNet will be highly suitable for real-world EV charging management situations where both high-quality prediction and resource efficiency aspects together can be met while allowing the model to be deployed with no or very minimum efforts.

7.6 Discussion of Multi-Domain Dataset Integration

Indeed, the lead impact of this study is the validation that our constructed multi-domain dataset integration framework can significantly enhance electric vehicle (EV) charger-type prediction. The tests outcomes revealed that in all three machine learning methods that the highest predictive performance was achieved by models trained using the integrated dataset as opposed to the use of separate behavioral, infrastructure, or market datasets.

The reason prediction accuracy improved is that the nature of integration results in a complementary mix of the original datasets. Behavioral datasets can very well capture charging behavioral patterns through features such as charging duration, energy consumption, arrival time, departure time and charging frequency. While these behavioral variables help us understand the types of charging sessions from an operations perspective, they hardly tell us anything about the physical charging infrastructure. On the other hand, infrastructure related datasets show information about the characteristics of a charger, its power level, connector type, station capacity as well its geographic location. Thus, the prediction models can learn about the technicalities of the charging points. Besides, there is also a market-related database that provides additional market-related data features like regional EV registrations, charging stations density, local population distribution and market growth as a region-wise determinant of charging demand. So, together these heterogeneous types of features provide a much richer and more comprehensive depiction of the EV charging scenario at an aggregated level than that obtained from any one of the original datasets.

XLM-RoBERTa produced its best classification accuracy when operating on the integrated dataset, suggesting that transformer-based contextual learning can derive great benefits from additional heterogeneous information. Likewise, TabNet exhibited better classification results after merging features from different domains, providing further evidence that sequential attention mechanisms work well in identifying valuable variables across heterogenous datasets. In fact, LightGBM, although relatively lower-performing, also experienced a notable rise in classification accuracy post multi-domain integration.

Thus, even simple gradient boosting machines are shown to be capable of benefiting from enhanced feature sets. All of these results imply that performance improvements are majorly due to the implementation of the new feature integration strategy and not a result of any specific machine learning model.

Models trained on individual datasets might be overfitting one particular domain and therefore when demonstrated on new changing environments, they might underperform. The proposed framework successfully combines several types of information behavioral, infrastructure, temporal, and market which serve to expose the learning algorithms to a broader range of charging characteristics, which are the main source of differences in user behavior, station configurations, and regional market conditions. The end result is the development of models that are more robust and better suited for geographical regions and charging networks by virtue of the training they have received.

7.7 Comparison with Existing Studies

To assess the potential advantages of the multi-domain machine learning framework proposed, we carefully examined the performance of our solution with respect to previous works on charging prediction in a similar research field. For the most part, researchers have concentrated on using one or the other approaches: either classic machine learning strategies or deep learning techniques with each study employing only one-domain data. The kinds of the data used were for example charging session logs, charging station details, or electricity bill information.

Despite their fairly satisfactory predictiveness, these procedures have shown limited transferability across different types of charging infrastructures due mainly to the absence of combined behavioral, environmental, and market data in each one of them.

According to the results gathered during the study, it turned out that the suggested approach, in which different types of datasets were combined together and a complex machine-learning architecture was used, led to a great improvement in the results of the predictive models for EV charger-type prediction models. Among the models we considered, XLM-RoBERTa proved to have the highest classification accuracy, with TabNet and LightGBM ranking second and third, respectively. What this shows is that a combination of contextual learning through transformers and multi-domain feature fusion is a very fruitful one that leaves the traditional approaches of gradient boosting and statistical machines in the dust.

In essence, this research mainly attempts to address gaps in the literature highlighted by different studies indicating various limitations like insufficient availability or diversity of datasets, limited comparison of models, no analysis of reliability issues, and also ignoring the aspect of deployment. Therefore, with such efforts, this EV charger-type prediction framework could be a significant leap forward within that domain.

7.8 Practical Implications of the Proposed Framework

This multidomain AI-based learning method introduces a way to radically change the electric vehicle charging system that is interconnected with smart networks and urban transit infrastructure design. Forecasting and identifying the types of chargers needed and their quantities precisely through demand is an effective and optimal planning tool which charging network operators can use to enhance facility usage, reduce the charging waiting time, and provide better control on energy distribution and ultimately a great user experience.

Through the framework's detailed forecast of charging demand, a decision-maker gets a complete picture of the situation including contextualized and operational dependencies that are mainly because of the comprehensive nature of the integration of charging user behavior, and charging infrastructure characteristics, and market-level dynamics.

Probably the clearest indicator of the usability of the proposed framework is found in charging infrastructure planning which the framework helps. Government agencies, urban planners, and EV charging station operators are able to make predictions and they will benefit a lot by making forecasts as one of the planning instruments. For example, they can use it to identify the under-serviced areas already considered for charging stations by other tools as potential new location and to assess the types of chargers to be deployed at each future site. This way the potential for capital waste is reduced and, at the same time, an optimal use of capital for capital-intensive infrastructure development is made possible.

A key issue is whether the deployed system will be up to the standard. While XLM-RoBERTa is the best-performing model in terms of accuracy, TabNet provides a well-balanced compromise between the time to compute and the prediction accuracy which makes it a suitable model for use on an online charging management system. When it comes to resource-limited scenarios like edge computing, LightGBM, with its fast computational capability and low memory consumption, can be the solution. In summary, the proposed framework allows varying the level of resources consumed for different purposes, and this could lead to different deployment scenarios. Thus, by adjusting the resources used appropriately, it will be possible to meet diverse needs within different EV charging scenarios.

7.9 Limitation of the Study

Relying on publicly accessible datasets from dissimilar geographical locations was one of the key aspects of this research. Due to the huge differences in factors such as habits and types of transport in different parts of the world, these datasets offer sufficient diversity in charging characteristics but do not revise fully represent all possible locations and their different weather and infrastructure. Therefore, this may lead to the need for further validation of the developed models before putting them into use especially in environments that are very different from the ones on which the models were trained.

The other point concerns the choice of features while developing this framework which was most oriented towards behavioral, infrastructure, temporal, and market-based data. Nevertheless, there are several other factors that may have a significant impact on the prediction that were not taken into consideration simply because of the lack of data, e.g., weather conditions, battery health, driver preferences, electricity pricing, renewable energy availability, and traffic congestion. Their inclusion would certainly be a subject of further improvement and enhancing the generality of the models.

Despite the fact that XLM-RoBERTa was the highest performer concerning classification accuracy, it has a very high computational requirement compared to LightGBM and TabNet which are faster to run. Deployment on low-resource edge devices without resorting to additional optimization methods such as model compression, pruning, or knowledge distillation, may be limited by this.

Another one has to do with the evaluation procedure. Experimental work was largely dedicated to offline evaluation on historical datasets in this study. More aspects of model's properties such as its adaptability or long-term robustness in real-time operation with continuously changing charging conditions were not considered. This means that there is still scope for experimental evaluation of the proposed framework in the charging networks used daily.

Moreover, the proposed ensemble model's weights, which were optimized, were kept constant based on offline experiments only. It has been suggested in the literature that changing weights under dynamically varying charging conditions feature the potential to essentially improve performance. Such adaptive strategies are to be the focus of future research efforts.

CHAPTER EIGHT

CONCLUSION AND FUTURE WORK

8.1 Contribution of Research Findings

This study proposed a multi-domain machine learning framework for electric vehicle (EV) charger-type prediction. It integrated behavioral charging data, charging infrastructure characteristics, temporal information, and market-related features into one unified predictive framework. It pointed out and addressed the limitations of existing EV charging prediction, which mostly uses single-domain datasets and only a limited range of machine learning algorithms. By combining multiple types of information, this study also compared three models: transformer-based, attention-based, and gradient boosting to find a comprehensive and scalable solution for intelligent EV charging prediction.

One major contribution of this work is that it has come up with a multi-domain dataset integration framework capable of merging disparate charging-related information into a single feature representation. The model training results revealed that an integration method for charging data collected from different domains significantly enhanced the predictive accuracy of all the models considered. It was also confirmed that behavioral, infrastructure and market features GeProvide complementary information for charger-type prediction. In this way, the feature fusion method developed by the study is a big step forward to single-domain prediction approaches.

Besides the study attempted a rigorous comparison of three state-of-the-art machine learning frameworks, namely XLM-RoBERTa, LightGBM, and TabNet, under comparable conditions. The outcome of the analysis clearly indicated that transformer-based contextual learning had the greatest accuracy, while TabNet offered an efficient compromise between prediction accuracy and computational speed. LightGBM, on the other hand, while delivering lower classification accuracy, showed excellent computational efficiency and could be considered a good candidate in situations with limited resources.

Developed framework checks the quality of a prediction against Accuracy, Precision, Recall, Weighted F1-score, Macro F1-score, ROC-AUC, confusion matrix analysis, confidence calibration, and ensemble weight optimization. All these methods of complementary evaluation present combined and in-depth judging of model competency and readiness for deployment, which is lacking in most of the literature on EV charging prediction.

In addition the framework is useful practically as the proposed support system for characterization and delineation of charger related attributes and characteristics for intelligent transportation system charging infrastructure development monitoring and operational issues forecasting of charging demand and its temporal pattern management of smart grid by providing the demand-response signal emission planning of new charging stations and their type allocation thus the decision-support systems for smart charging of electric vehicles and other related problems of the electric vehicle sector.

Besides, this modular design can be extended by integrating other heterogeneous data sources in developing intelligent EV charging applications in the future.

8.2 Addressing Research Objectives

This work has fulfilled the objectives set out in the introduction by successfully developing, implementing, and validating the multi-domain machine learning framework.

Objective 1: To investigate the influence of behavioral, infrastructure, temporal, and market-related information on EV charger-type prediction.

This goal was realized via a thorough collection of data sets (from the public sources available online), preprocessing, feature engineering, and combining several domain-specific data sets into a homogeneous data set. The results of our experiments have shown that combining different types of information considerably helps prediction accuracy. Thus, multi-domain learning is much more effective than learning based on a single domain.

Objective 2: To develop a unified multi-domain machine learning framework for EV charger-type prediction.

A unified prediction framework integrating multiple heterogeneous datasets was successfully developed. The proposed framework enables the simultaneous learning of charging behavior, charging infrastructure characteristics, and market information within a single predictive model.

Objective 3: To evaluate the predictive performance of advanced machine learning models.

Three advanced machine learning models XLM-RoBERTa, LightGBM, and TabNet—were implemented and evaluated under identical experimental conditions. The comparative analysis demonstrated that XLM-RoBERTa achieved the highest predictive performance, while TabNet and LightGBM provided competitive alternatives depending on computational requirements.

Objective 4: They experimented to examine the extent to which combining features from different domains can be effective.

The results of the research showed that combining different datasets consistently led to an enhancement in prediction power for all models examined. This indicates that our multi-domain feature merging method was correct and shows its good applicability for intelligently predicting the charging of electric vehicles.

Objective 5: Checking whether smart EV charging systems are ready for deployment.

Deployment readiness was tested with a suite of metrics: computational efficiency analysis, reliability calibration, ensemble optimization, and comparative model evaluation. The results suggest that the model is flexible enough so it can be deployed in cloud computing, edge computing, as well as intelligent charging infrastructure management systems.

8.3 Limitations of the Study

Despite the fact that this method delivered good results the authors are not entirely satisfied. For example, the first problem concerns the fact that the data in the paper are from different countries but not all of them. These datasets, although diverse in nature, still lack coverage of certain regions, different customer groups or types of charging stations, and the effects of climatic changes on users.

Firstly, the research used public datasets collected from different parts of the world. Although these data sources offer a great variety, they might not fully capture charging habits from countries, climate zones, types of charging stations, or different user segments. More tests with charging data collected at the local level would help to make the models more generalizable.

Secondly, the framework under discussion gave more importance to variables such as user behavior, infrastructure, time, and market. Other factors known to have a major impact, for example, conditions of weather, electricity price, production of green energy, traffic situation, battery condition, vehicle telematics, and user mobility behavior, were not considered due to data scarcity.

Third, even though XLM-RoBERTa was the best-performing model, its computational load is still considerably more than that of LightGBM and TabNet. Therefore, carrying out a transformer-based solution on devices with limited resources will most probably necessitate the use of optimization methods like model pruning, quantization, or knowledge distillation.

Yet another limitation relates to the evaluation approach. Historical datasets were used for the experiments, so the studies were executed under offline experimental settings. Of course, continuous online learning and real-time placement of the charging networks would have been practical, but they are unexplored topics in these studies. Therefore, looking into long-term adaptation to the charging environment change is a cool thing to do!

Lastly, an element of ensemble learning with fixed optimized model weights that were obtained through offline optimization was introduced here. Dynamic ensemble learning methods that can automatically adjust model weights according to changing charging conditions are likely to result in further performance improvements.

8.4 Future Research Directions

Here are some suggestions for future work following the development of this study area.

Several heterogeneous data like weather, renewable energy generation, electricity market prices, traffic condition, battery deterioration indices, electric car telematics, and user mobility traces, should be a part of the upcoming research. We hope that the adding of such parameters will lead further improvement of the forecast accuracy and model robustness respectively.

Exploring state-of-the-art artificial intelligence techniques may open up a very promising avenue for future research. Some research topics could include experimenting with graph neural networks, temporal graph transformers, multimodal transformers, foundation models, or hybrid deep learning frameworks that are capable of grasping diverse EV charging situations.

A different approach that would equally merit researchers is the concept of developing continuously adjusting prediction models. These models can be automatically recalibrated whenever new data samples are made available, thus they should have a dual effect: increasing prediction accuracy and decreasing model performance degradation that are results of charging behavior fluctuations and the development of the charging infrastructure.

On the other hand, researchers are expected to think of the artificial intelligence systems which are of not only highest performance but also lowest computational resource requirements that could be operated in a charging network by deploying at charging stations and edge devices respectively. It is the model compression, quantization, knowledge distillation, and edge AI optimization approaches that the researchers may find very useful in achieving this goal.

For the model users to understand the workings and trust the model, XAI has to be the core concept of the work with artificial intelligence where explainability is a central point. The most effective of these techniques are SHAP, LIME, Integrated Gradients, and attention visualization in providing feature explanation and also helping the EV charging network managers and the policymakers in taking their respective decisions.

Lastly, it is a good idea to run large-scale real-world field trials in a range of countries utilizing different classes of charging facilities in order to determine how effective, flexible, and easy the proposed system is in practice. Such real-world applications will clearly show the value and usefulness of the prediction system to be employed in the EV charging stations of the coming age.

8.5 Conclusion

This study described a multi-domain machine learning framework that combined user charging behaviors, characteristics of charging infrastructures, time information, and market factors into one model for predicting which type of electric vehicle charger would be used. Our approach to this problem is very different from what has been done before, as we allow the machine learning algorithms to extract and combine complementary features from various heterogeneous datasets simultaneously.

We implemented the three most up-to-date machine learning technologies, namely XLM-RoBERTa, LightGBM, and TabNet and carried out their tests under the same set of experimental conditions. Comparison of the results showed that, thanks to its transformer-based contextual learning, XLM-RoBERTa outperformed others in terms of accurate prediction. Meanwhile, TabNet was able to strike a good compromise between accuracy and computational cost. On the other hand, LightGBM surpassed the other two in terms of computation time and is still recommended for use in resource-constrained scenarios. Additionally, the experimental data revealed that the multi-domain dataset integration framework proposed in this study significantly boosted the prediction capabilities of all the models, thereby providing strong support for the main proposition of the research.

The new framework is a dual-discipline contribution, advancing scientific knowledge and also serving the needs of real intelligent transportation systems. This technique is unique and very thorough in the way that it can predict different aspects of EV charging. It uses data from many sources related to EV charging, advanced machine-learning methods, evaluates the predictions in great detail, and then it gives an analysis of how all of this can be implemented in the system. Among all these aspects, charging infrastructure planning, charging demand forecasting, smart grid integration, charging station design, as well as intelligent decision support systems are the areas that the framework can significantly benefit.

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