CROWDING REDUCTION AND WAITING TIME ANALYSIS IN HEALTH-CARE SYSTEM USING MACHINE LEARNING

by

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To my mother, father, and wife,

To my beloved daughters Lilian and Savanna

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Hassan Mohmmed Hijry

ABSTRACT

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In the hospital setting, the emergency room (ER) offers timely emergency care for patients and is considered the busiest department because of the urgency of cases. Emergency rooms have the highest number of patients overcrowding within any hospital; more than 50% of the patients admitted to the hospital come through the ER. Healthcare management is continuously trying to minimize wait times and optimize the hospital's allocated resources, but most ERs still suffer from the overcrowding crisis due to the stochastic arrival and random arrival distribution. Advanced techniques, such as machine learning algorithms, are useful for determining real life queue scenarios and patient flow (e.g., waiting time in queue and length of stay), which are considered measures of ER overcrowding. As such, we began by building a model to predict patient length of stay through predictive input factors such as patient age, mode of arrival, and patient's type of condition using three machine learning algorithms (e.g., artificial neural networks (ANN), linear regression, and logistic regression). The best model accuracy ANN resulted in an increase of 19.5% compared to the performance from previous studies. Then, the Deep Learning Model was applied for historical queueing variables to predict patient waiting time in a system alongside, or in place of, queueing theory (QT). Four optimization algorithms (SGD, Adam, RMSprop, and AdaGrade) were applied and compared to find the best model with the lowest mean absolute error. The results showed that the SGD algorithm achieved better prediction accuracy than the traditional approach and reduced the use of assumptions. Moreover, the model decreased the error reduction by 24% when compared to prior literature. Lastly, we proposed a model to predict the patient waiting time based on the lab test results. Multi-algorithms were implemented by using real-life COVID-19 test results data recorded during the pandemic. Among the eight proposed models, the results showed that decision tree regression performed better for predicting waiting times. Based on experiments performed in the research, this dissertation provides a guideline for waiting time analysis in the queue—not only in healthcare, but also in other sectors, considering model understandability and the feature extraction process.

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LIST OF ABBREVIATIONS

ER	Emergency Room
LOS	Length of Stay
ANN	Artificial Neural Networks
DL	Deep Learning
IoT	Internet of Things
EHR	Electronic Health Records
EDs	Emergency Departments
LOINC	Logical Observation Identifiers Names and Codes
NLM	United States Library of Medicine
CDSS	Clinical Decision Support Systems
RxNorm	Standard for Representing Medications
DICOM	Digital Imaging and Communication in Medicine
ICD	International Classification of Diseases
WHO	World Health Organization
DRG	Diagnosis Related Group
CAP	College of American Pathologists
SNOMEDCT2	Systematized Nomenclature of Medicine-Clinical terns
RBM	Restricted Boltzmann Machine
CNN	Convolutional Neural Nets
FEMTALA	Federal Emergency Medical Treatment and Labor Act
EMS	Emergency Medical Services

RF	Relevant Feedback
KNN	K-nearest Neighbor
DT	Decision Tree
CNN-MDRP	Convolutional Neural Network-based Multimodal Disease Risk Prediction
NB	Naïve Bayesian
SVM	Support Vector Machine
SLs	Surveillance Levels
ML	Machine Learning
AI	Artificial Intelligence
CA	Cardiovascular Autonomic
RPROP	Resilient Backpropagation
GBM	Gradient Boost Machine
RF	Random Forest
MLP	Multilayer Perceptron
MLF	Multilayer Feedforward
BP	Back-propagation
BPN	Back-Propagation Neural networks
SGD	Stochastic Gradient Descent
RBFN	Radial Basis Function Network
MSE	Mean Squared Error

ICU	Intensive Care Unit
MAPE	Mean Average Percentage Error
NLLSR	Linear Least Square Regression
MLR	Multiple Linear Regression
CAD	Coronary Artery Disease
LR	Logistic Regression
CART	Classification and Regression Tree
SOFM	Self-Organizing Feature Maps
MDS	Multidimensional Scales
HCA	Hierarchical Cluster Analysis
ACS	Acute coronary syndrome
ALC	Altered Level of Consciousness
P	Pulmonary oedema
HB	Heart blockage
acc	model accuracy
QT	Queuing theory
RSS	Random Service Selection
MAE	Mean Absolute Error
ReLU	Rectified Linear Unit
ADAM	Alternating Direction Method of Multipliers

Adagrad	Adaptive Gradient Algorithm
RMSprop	Root Mean Square Propagation
DES	Discrete Event Simulation
QT	Queueing Theory
MAE	Lowest Mean Absolute Error
SGD	Stochastic Gradient Descent
Adam	Adaptive moment estimation
RMSprop	Root Mean Square Propagation
AdaGrad	Adaptive Gradient
ReLU	Rectified Linear Unit
LR	Linear Regression
SVR	Support Vector Regression
NN	Neural Network
KNN	K-nearest Neighbor Regression
GBRT	Gradient Boosting Regression
ET	Extra Trees Regression
DT	Decision Tree
RF	Random Forest
MSE	Mean Square Error
RMSE	Root Mean Square
EDA	Exploratory Data Analysis

PCA	Principal Components Analysis

CHAPTER ONE

INTRODUCTION

1.1. Motivation

In 2017, the government of Saudi Arabia launched a plan, known as Vision 2030, aimed at improving the general healthcare of citizens and, specifically, Hajj people. However, the hospital system, especially emergency departments (EDs), continue to suffer from overcrowding and long patient stays, even when the required procedures are small. To ensure that the Vision 2030 goals can be achieved, those involved should be ready to adopt a model for a smart healthcare system [1]. This will mostly depend on standards that are fit for international ratings and include compiled strategic planning of the smart city system using the examination of the current situation in the healthcare system. Then, using the results from the examination, they can adopt a series of scenarios using advanced technology to meet future plans.

The development of the healthcare system has long been based on implementing the most current information and communication using new technology [2]. For example, some systems can be used like interactive databases, collecting data on any given day using the Internet of Things, Big Data, and Machine Learning. Healthcare also analyzes data by studying artificial intelligence, which has proven to be very beneficial; they extract this data and use it in decision-making processes. Mecca, Al-Madinah Al-Munawara, and other holy places have a vision of adopting smart city grids. These areas suffer from severe crowding and other unfavorable metropolitan characteristics [1]. These places are deeply entwined with Muslim culture. As such, extra attention is provided to the privacy needed at given locations, times, and activities conducted by residents and visitors of these holy cities, as well as the needs they have. This all depends on a different axis; the human axis is viewed as the major axis in the system because humans are associated with education and health service needs. These cities must improve to meet the needs of the vast number of people who visit each year, including the reduction of emergency department overcrowding.

The growth of information, communication, and technology have led to the significant development of smart cities, which have several working components, one example being a smart hospital. The smart hospital is used to improve the healthcare system and to provide extra and different services to the patients. These services may include early diagnostics and comprehensive care. In this technological era, there are many machine learning techniques (smart approaches) that can be used to facilitate and improve health care services. The use of electronic health records and other electronic services is an example of what is expected from the smart city plan in the healthcare system so that improvement can be spotted. The use of these variables can also support self-diagnosis, how treatment is conducted, and the early detection and prediction of diseases.

1.2. Crowding Problem in Emergency Departments

Over the past years, many hospitals across the world face overcrowding in their EDs on a regular basis. Overcrowding mainly happens when there is a concurrent lack of healthcare providers and a high demand for medical services. The number of visits to EDs increases gradually every year in the United States [3]. A 2007 report published by the Institute of Medicine conducted that in the United States, visits to EDs s were reached by around 114 million annually. Additionally, at that time, ambulances drove 16 million patients to the ED [4].

A year later in 2008, another report was issued by the American College of Emergency Physicians. This report was aimed at developing and putting into action effective solutions to the crowding problem in EDs, particularly in four states between 2008 and 2009 [5], [6]. Recently, in 2016, the National Center for Health Statistics surveyed visits to the ED approximately 145.6 million annually visits [7]. Not only have ED visits increased, but so has waiting time. In 2018 the Canadian Institute for Health Information reported the waiting times in ED had noticeably increased since 2015 [6].

Emergency department overcrowding is one of the most significant problems in healthcare worldwide. This is due to its numerous negative effects on public health, at both the international and local levels There are internal and external factors that contribute to ED overcrowding, such as a shortage of healthcare specialists (e.g., staff, physicians ,and nurses) [8] and waiting for a patient to be admitted [5]. Such consequences of these factors can risk the lives of several patients [9].

In general, long waiting times in the ED can make patients undergo poor experiences, which eventually drives them to depart without being examined. Also, patients might avoid seeking healthcare services from the ED again. Figure 1.1 shows the patients' interest over the last five years in seeking ED services due wait times. This data was gathered by Google trends data from 2014 to 2019. The numbers represent search interests relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. Also, a score of 0 means the term was less than 1 % as popular as the peak. Source: (trends.google.com). Relevant surveys have stressed the fact that ED crowding brings about irritating waiting times, during which patients suffer while waiting for different types of healthcare services, such as imaging, lab testing, and medical assessments, etc.,[10], [11].

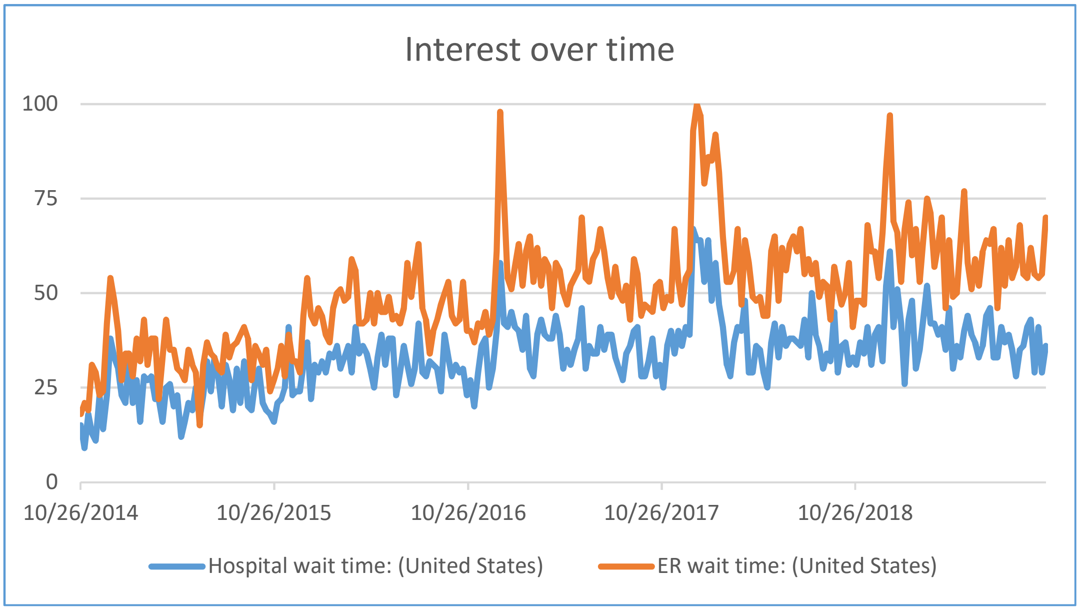

Figure 1.1. ED wait times search query over Google trends.

Another consequence of wait times is the need to transfer to another healthcare institution where the ED is not crowded [12]. Patients are fed up with ED crowding because it makes them face delayed admission and hence delayed healthcare services [13],[8].

Other common consequences arising from ED overcrowding are higher rates of disease infection, longer stays at hospitals, more frequent fatal medical errors, and an increased number of deaths among patients [14]–[16]. In [14], the authors noted that if the care team collaborated and developed effective strategies for the ED system, it would have a significant effect on patient flow. This issue causes worries not only for negative effects on throughput but also for adversely affecting all individuals in need of emergency services, doctors, the healthcare institution itself (hospital, medical center, etc.), and the quality of healthcare services [9]. That would result in late healthcare assessments and delayed healthcare services.

Additionally, ED overcrowding frustrates care professionals and makes them less satisfied with their jobs and workplaces. Job dissatisfaction can scale down the productivity of healthcare staff and scale up their turnover [9]– [11]. As a result, patients may suffer due to a lack of efficiency. The decrease in the productivity and stability of human resources in EDs can play a role in increasing the rates of fatal medical errors, affecting the lives of millions of patients. Overcrowding usually causes the patient to stay for a long time in the ED, which results in a long queue of people needing to be seen by a physician. This research focuses uniquely on overcrowding factors that are known to potentially influence ED wait times, which are essential to developing an accurate ED queueing model. More recently, there has been theoretical work in patient waiting time prediction in emergency rooms (ERs); however, these are limited due to accuracy, small sample size, and locality data collection (Curtis et al., 2018, Pak et al., 2020, and Wynants et al., 2020).

1.2.1. Causes of ED Overcrowding

Several research studies have been conducted to establish the causes of overcrowding. Many discuss the causes and offer feasible solutions that can effectively address the root causes. Research in overcrowding is important to the efficient provision of healthcare services as well as to better understand the impacts of overcrowding.

According to studies, ED overcrowding is a multifactorial problem. A cited cause is an inadequate number of inpatient beds. According to recent research studies into the phenomenon, the rising number of patients admitted against limited bed-spaces in most facilities is the number one cause of overcrowding [17]–[19]. Additionally, this inadequate number of critical care beds has been cited as the potential cause of high acuity patients being stranded in the ED, thereby limiting access and increasing waiting times for other individuals who need immediate care.

Besides lacking an adequate number of inpatient beds, another cause of ED overcrowding is delays during diagnosis and imaging [12], [17], [20]. This delay results in an accumulation of patients based on the incoming against the already served and outgoing patient numbers. To add on that, understaffed EDs and increasing volumes of high acuity patients are two other causes of overcrowding [21].

One goal of most hospitals' emergency departments is to provide high acuity patients with effective emergency care. Conversely, most ED visits are patients with non-urgent ailments which increases ED occupancy. Therefore, studies have tried to establish whether low acuity patients contribute to delays in the provision of healthcare to high acuity patients through resource diversion from an immediate care need to a non-emergency case. However, a study conducted in Ontario involving 2.2 million patients from 110 EDs established that low acuity care has an insignificant impact on overall ED length of stay and time to treatment of a high acuity patient [22]. The findings of this study might be explained by the fact that most hospitals' emergency departments have a "Fast Track," which is a rapid assessment area to establish the urgency of incoming cases [23]. Therefore, such interventions have helped hospitals to reduce the waiting time and length of stay for low acuity patients, thereby reducing ED Overcrowding. The Fast Track is applauded for setting priorities and enhancing efficiency in the treatment of patients with low acuity and non-life threatening conditions [23] as well as resulting in increased patient satisfaction.

Another potential cause of ED Overcrowding is the implementation of the Federal Emergency Medical Treatment and Labor Act (EMTALA) of 1986, which stipulated that a patient can seek ED treatment irrespective of their ability to pay, thus leading to ED overcrowding with non-life threatening conditions [24]. Therefore, since the ED has become the most preferred option for most patients without medical insurance or those unable to seek other healthcare options, the ED has become overcrowded [25].

Various studies have used different variables to determine the causes of ED overcrowding. Consequently, different outcomes have been arrived at because of the different variables used. Table 1.1 shows the outcome of different studies in relationship to the ED overcrowding.

Table 1.1. Causes used in studies of ED crowding.

	Felton (2011)	Boyle (2012)	Erenler (2014)	Li (2015)	Cai (2016)	Mirza (2018)	Abe (2019)	Ülkü (2020)
Patient acuity						✓		
Imaging and test results		✓	✓	✓				
Patient diagnostic		✓	✓	✓				
Patient Volume								✓
Access to consultants								✓
ED occupancy	✓		✓		✓			
Understaffing the ED								✓
Queuing Delay		✓					✓	

1.2.2. Impacts of ED Overcrowding

ED Overcrowding not only impacts the time and length of stay for high acuity patients, but also impacts the overall quality of care in hospitals. The impacts of ED overcrowding, therefore, become an economic burden on hospitals [26]. During overcrowding, all available spaces are taken up as additional patients in need of emergency care are directed to waiting halls [27]. With the crowded ED and the waiting patients, the health care provision quality is significantly reduced, thus posing high risk to patient health.

A report on long wait times for treatment by the Center for Disease Control and Prevention states that the median treatment time was 90 minutes for all patients [28]. With such prolonged times, there is likely to be delayed medical intervention which, if not checked, leads to severe pain experiences in patients, thereby threatening their health status [29].

Prolonged waiting time has an impact on patient satisfaction [30], [31] as well. Generally, waiting a long time while in severe pain leads to frustration and feelings of disappointment in the ED, its staff, and its services [32]. In some instances [4], [30], the frustrated patient leaves for another facility or goes home without receiving treatment—a situation that leads to higher health risks for the patient as a result of ED overcrowding. The cumulative impact of ED overcrowding is that the number of patients who leave without treatment return at a later date, contributing to even more overcrowding. Patients who leave without treatment and then seek to return at a later date are at higher risk of adverse disease and worse outcomes when compared to those who wait until attended to and discharged [33]. Therefore, it is suggested that effective communication with patients about the estimated wait times before treatment can help manage expectations and encourage people to wait for care, thereby reducing later adverse events and outcomes [34].

Another approach being used by EDs is the diversion of ambulance services to other EDs when there is persistently high patient traffic in one facility. Unfortunately, this approach does not solve the problem but creates another problem. The rerouting only provides a temporary break in ED traffic to address the existing patient load [35]. One implication of Emergency Medical Services (EMS) rerouting is loss of revenue as well as the creation of a behavior where the nearby facility also redirects its ambulances, thus causing system clogging, creating a domino effect [30]. Moreover, studies have linked ambulance diversion to adverse impacts on patient safety due to increased transition time when a patient on an ambulance who requires immediate care is diverted before arriving at the ED [36], [37].

1.3. Research Objectives

In 2017, the Saudi Arabian government launched a plan called 2030 Vision to improve the health care in general. It specifically targeted better care for Hajj patients, but the systems in hospitals—specifically in EDs—still suffer from overcrowding and LOS, even for small operations. As such, this research has three objectives:

Objective 1: This research attempted to improve the ED system using machine learning techniques to provide a better service for Hajj patients analyzing the LOS. One of the benefits of accurate LOS assessment is proper resource allocation and efficient utilization of resources by ED management. Additionally, forecasting and determination of LOS in hospitals helps in prioritizing health care policies and promotes health services by the hospital management, accurate and appropriate allocation of health care resources based on determined LOS while considering patients' health status, and social demographic features. For this reason, in this dissertation, a model built for forecasting LOS of Hajj patients using machine learning algorithms within the predictable input factors, such as age, mode of arrival, number of patients, gender, provisional diagnostic category, ICU admission, and number of comorbidities are presented in Chapter 3.

Objective 2: This study applied DL algorithms (chapter 4) for historical queueing variables to predict patient waiting time in a system alongside, or in place of, queueing theory. Queuing theory (QT) is a traditional mathematical technique that has been used to analyze queuing systems for decades. However, the traditional approach may not be sufficient in real life applications because the methodology is limited, for example, unrealistic assumptions of the time distribution it requires to do queueing analysis. Thus, alternative techniques, such as deep learning (DL) algorithms, are considered to significantly improve ER efficiency.

Objective 3: This research sought to predict patient waiting times (chapter 5) using lab test results, reduce the error prediction and achieve better accuracy, when compared with prior studies in literature. The ability to accurately predict the waiting time for lob test results may increase patient satisfaction and effectively improve the healthcare system. This improvement will be accomplished by predicting the waiting times for lab test results based on predictive factors such as test location and labs where patients took the test (as queues or lines for patients). Even though the patients are not in a physical line, they still count as people waiting for service to be finished.

1.4. Dissertation Outline

In this dissertation, we analyze the crowding problem in the ER by studying different factors reported by hospitals, which may affect overcrowding using different machine learning algorithms. We start in Chapter 2 by reviewing different topics under the main topic of this dissertation to provide background information. Then, we start investigating the single variable of patient length of stay (LOS) in Chapter 3. Subsequently, we investigate another isolated variable, patient waiting time in queue, using deep learning (DL) technique with multi-optimization algorithms in Chapter 4. Finally, in Chapter 5, we propose a model to predict the patient waiting time based on lab tests and by implement multi-algorithms and using real-life COVID-19 data recorded during the pandemic.

CHAPTER TWO

BACKGROUND

2.1. Electronic Health Record

Digitally stored patient history records are known as Electronic Health Records (EHR). The main purpose for digitizing patient health records is to ensure the effective planning of patient care, to set healthcare objectives, document healthcare delivery, and ease assessment of the services outcomes [38]. Electronic health records data records educate controlled vocabularies, and the data are handled over all aspects of care over time [39]. Electronic health records not only help by streamlining workflow in a medical setting, but also automates data management. The unstructured text, structured, coded data, and time-stamped events are the major components of an Electronic Health Record. Therefore, EHR is an aggregation of data generated by each element and thus can be used in:

1. Diagnosis and prognosis by physicians
2. Administrative purposes, such as billing and reimbursement systems
3. Resources by researchers to gain knowledge in the medical field

The adoption of EHR in healthcare was primarily to facilitate and promote the exchange of information among different healthcare settings. The seamless exchange of information however, requires coding standards in four major areas [40]:

1. Interaction with users
2. System communication
3. Information processing and management
4. Consumer device integration

Administrative data, which is primarily characterized by socio-demographic information about patients, medical reports, and summaries, make up the largest information stored in Electronic Health Records. Thus, they are used for administrative purposes. The EHR generates unique identifier links specific for each patient and links the patient's data to different EHR components. The data can be stored in narrative text, especially clinical data detailing patient's treatment plans and summaries. Besides that, it can store in clinical tests results, medical images from radiology, and medication and dosage instruction from the pharmacy.

2.1.1. EHR Coding Systems

The EHR has defined standards which are used for recording, storing, and transmitting data from each of the EHR components. Moreover, the Electronic Health Record has a coding system that handles medical data. Some of the common coding systems applicable in four areas of application of EHR include:

LOINC- LOINC is an acronym for "Logical Observation Identifiers Names and Codes". It provides terminology to identify clinical results, such as laboratory tests, clinical observations, outcomes management, and research. Each record is represented by a single test result consisting of: components measured, component characteristics, measurement method, component specimens, measurement scales, and measurement time [41].

RxNorm- RxNorm was developed by the United States Library of Medicine (NLM) and it is a terminology standard for representing medications. RxNorm includes medication name, dosage, route of administration, ingredients, and pharmacy prescription [42]. The terminology is used in standard nomenclature to capture or record drug information from EHRs; it is used in facilitation of data exchange among providers; and in facilitation of medication related to clinical decision support systems (CDSS) [42], [43].

DICOM- Digital Imaging and Communication in Medicine (DICOM) deals with standard handling and transmission of medical images. Accordingly, it defines the file format and network communication protocol for biomedical images [44].

International Classification of Diseases (ICD) – ICD is the official coding for standardizing disease and health-related information exchange. It was introduced by the World Health Organization (WHO) as a system of codes covering diseases and related problems, social circumstances, and external causes of injury or diseases.

Over the years, it has been revised several times. The previous ICD-10 was released in 1994 and covered more disease and diagnosis codes and was more efficient as compared to its immediate predecessor, ICD-9 (ninth version), which was released in 1978 and was the most popular [40]. Countries such as Australia have its own version of ICD-10 by adding the country's specific codes. Version ICD-11 was released in 2018 [45] and it is the most current version.

Diagnosis Related Group (DRG) – DRG is used for classifying patients into predefined groups based on treatment data before relating them to the cost incurred by the hospital [46]. The groups are developed as part of the hospital reimbursement system with binding prices attached to each group. Additionally, DRG is used to define reimbursement amounts to the hospital from medical insurance systems such as Medicare.

SNOMED-CT- the College of American Pathologists (CAP) created Systematized Nomenclature of Medicine-Clinical terms (SNOMEDCT2) in 1965 [47]to encode medical concepts using inbuilt definitions and formal logic to represent data to be used for clinical purposes [48].

2.2. Modeling Electronic Health Record

While building learning models for an EHR, it is important to first derive desirable features reflective of the temporary nature of patient data. By nature, patient data in EHR are longitudinally structured and consist of various information. This information includes patient demographics, administrative details, clinical observations, and results recorded over time [49], and the information are fundamental for clinical decision-making processes [50].

Previously, a work-built system called RESUME was used and it focused on ontologies from medical domains along with temporal events from patient databases to create abstractions based on inference and interpolation [50]. Accordingly, an apriori-like technique with the ability to extract precedence frequency between episodes while employing the temporal variations association rule was proposed by Sacchi et al. (2007) to test on two different biomedical datasets [51]. Additionally, Batal et al. (2013) proposed a minimal Predictive Temporal Patterns framework capable of extracting predictive features from patients with blood disorders [52]. A case in [53] based reasoning to temporal abstraction for prognosis of kidney function and the spread of influenza was presented by Schmidt and Gierl (2005).

Due to inconsistencies and irregularities when modeling data using EHR, various deep learning techniques have been proposed. These include developing models to mirror the irregularities in event times and interventions. Deep learning approaches for clinical phenotypes and the discovery from irregular and sparse EHR data was pioneered by Lasko et al. (2013). Their data-driven method led to the discovery of accurate phenotypes as those engineered by a domain expert [54]. Using parametrizations over standard classifiers that use non-temporal features, Pham et al. (2016) were able to demonstrate the superior performance of both long and short-term memory [55].

Therefore, deep learning approaches have been used in feature extraction and representation of patient data from EHRs because of the significant steps that have been made in data representation in text and multimedia learning [56]. Moreover, a prominent work introduced the "Deep Patient" model to help capture patient data patterns using stacked autoencoders [57]. Using a study population of 700,000 patients, the study demonstrated superior prediction performance on 78 diseases, including cancer and diabetes. Med2Vec was introduced by Choi et al. (2016) based on the Skipgram model [58] to learn distributed representations over a million patient visits to provide clinically meaningful interpretations. Additionally, the Restricted Boltzmann Machine (RBM) was recently used to embed patient features from EHR into a vector space.

The results demonstrated superior performance as compared to clinicians in prediction of suicide risks [59]. The variations presented in RBM have also been used in profiling patients with applications in the study of disease correlations and risk prediction [60]. Convolutional Neural Nets (CNN) have also been used in deep learning architecture for clinical prediction to detect motifs from words and phrases in medical records, which are useful in predicting future risks in patients [61]. Accordingly, the modeling of patient flow is considered the most popular use of EHR.

2.3. Patient Flow Analysis

Cost and resources allocation per hospital always varies based on the length of patient stay. Therefore, long term projections in healthcare helps with bed modelling and the assessment of staffing needs over given periods, e.g., months and years. This information is crucial in administrative and clinical data in EHRs. According to Cote and Tucker (2001), the common methods in healthcare demand forecasting per adjustment are: 12-month moving average, trend line, and seasonalized forecasts [62]. The methods are built on historical demands while seasonalized forecasting considers seasonal variations and trends in the data, hence providing more realistic results.

On the other hand, Mackay and Lee (2005) advised on modeling the patient flow in healthcare institutions for tactical and strategic projection, for example compartmental, queuing [63], [64], and simulation models have been applied to analyses of patient flow [63]–[65]. Moreover, bed occupancy [64], [66], [67], patient arrivals [68], and individual patient length of stay metrics are analyzed to understand the long-term patient flow [64], [69], [70]. Thus, the key performance indicator metric in assessing quality of care is the most popular, and units with much interest placed on this are emergency or acute care departments [71], [72].

Therefore, the main categories of patient flow forecasting are: time series and smoothing methods of patient flow techniques, simulation methods, and regression methods. Machine learning methods, however, provide skillful techniques. Thus, machine learning is the key solution to all predictive modeling problems including patient flow forecasting models.

2.4. Patient Length of Stay Prediction

Length of stay (LOS) forecasting studies have previously applied prediction approaches such as artificial neural networks (ANNs), Logistic regression, and linear regression. However, little has been written about LOS forecasting including linear and nonlinear approaches in one model. Li et al. proposed a LOS prediction study, Back-Propagation (BP) neural networks with data mining approach [73]. The BP neural networks analyze 921 Chinese hospital cholecystitis patient's data treated between 2003 and 2007 with model accuracy of 80%. Five LOS predictors, days before the operation, wound grade, operation approach, charge type, and a number of admissions were used in the model.

Using ANN, Wrenn et al. [74], estimated the patient's LOS in the ED. The ANN was developed using a Stuttgart Neural Network Simulator software whilst using variables such as age, acuity level, coded ICD-9 chief complaint, language, order for a consult service, preference of at least one laboratory exam, and presence of at least one radiology examination of a patient, as well as other operational variables. Accordingly, the study concluded that ANN is a powerful tool applicable in the analysis of complex medical data such as emergency departments. Moreover, Xu et al. [75] used a data-driven method to identify variables correlated with the daily arrivals of the non-critical patients and models associated ANNs. To calculate the mean average percentage error (MAPE), ANN modeling is compared with the linear least square regression (NLLSR) and multiple linear regression (MLR).

Many models' applications show that linear and logistic regression perform better than other methods. The prediction of dementia diagnoses using variables was arrived at either through domain experts or statistically driven procedures as proposed by Mazzocco et al. [76], which applies prediction models that are based on logistic regression algorithm. Moreover, numerous studies in the field have also revealed that linear and logistic regression give good results. Therefore, Austin et al. [77] aim at improving the performance of the recent application of Bayesian Belief Networks by applying a logistic regression alternative approach.

Prediction of the presence of coronary artery disease (CAD) has been enabled through classification approaches. Accordingly, Landwehr et al. [78] compares the performance of the classification techniques; performance of logistic regression (LR); classification and regression tree (CART); radial basis function (RBF); self-organizing feature maps (SOFM); and Multilayer Perceptron (MLP). In addition, the performances of classification techniques were compared using a receiver operating characteristic curve as well as with Multidimensional Scales (MDS), and Hierarchical Cluster Analysis (HCA). Thus, rating the classification techniques based on effectiveness from superior to least superior are in this order: MLP, LR, CART, RBF, and SOFM technique.

In predicting in-hospital mortality rate of heart-failure patients hospitalized, Kurt et al. [79] compared the predictive accuracy of regression trees with that of LR models and concluded that LR are more accurate than regression trees. However, it was also noted that regression trees grown from random samples from the same data set differ significantly from one another. On the other hand, the authors appreciate that LR accounts for underlying linear relationships that exist between key continuous covariates, and the log-odds especially, in the prediction of in-hospital mortality.

Another strength of LR is its ability to produce a probability rather than prediction. For instance, for each class value, the technique produces an estimated probability that a case indeed belongs to a specific class; hence, the model is considered a state-of-art model.

2.5. Patient Waiting Time Prediction

Previous research shows that long waiting times lead to patient frustration, anger, anxiety, and dissatisfaction [80]–[82]. Several studies have applied different methodologies to analyze ER waiting time predictions. For example, Kuo et al [83] combined machine learning with systems thinking to predict waiting time in ER. Stagge (2020) implemented a combination of approaches including machine learning and a simulation to predict patient waiting time; [85] used multi machine learning methods, such as Elastic Net and Random Forest, to predict the waiting time for low patient acuity in ER. Finally, Curtis et al [82] developed multiply machine learning algorithms including neural network to predict patient waiting time considering different predictors, such as patient arrival time, complete service time, and examination.

Moreover, studies have designed predicting models to forecast the waiting time until treatment for patients with low acuity using algorithms, such as quantile regression [86]. Our study differs from the previous research on this topic because we implemented multi-DL optimization algorithms to improve accuracy. Furthermore, we considered different predictors by extracting new parameters from the patient joining the queue (e. g., minute, hour, and day), waiting time in the queue, and departure time.

Many hospitals across the world face long waiting times and crowding in their ERs on a regular basis. The number of visits to ERs increases gradually every year in the United States [3]. In 2016, the National Center for Health Statistics surveyed visits to the ER to be approximately 145.6 million annually visits [7]. Not only have ER visits increased but waiting times in the ER have as well. For example, the Canadian Institute for Health Information reported in 2017 that the waiting times in ERs have noticeably increased since 2015. Evaluating the efficiency of ERs is a viable way to solve these problems [87].

Some hospitals are using queuing models to enhance optimal allocation of their staff by assessing patient arrival times [88], [89]. A predicting model is becoming useful in the medical industry. Use of historical data to predict future patient waiting time is becoming a useful model for solving seasonal arrival and waiting times [90], [91]. The data saved in EHR are the key to solve and examine healthcare problems that might contain hidden features. Other studies have focused on queuing system improvements in healthcare, mainly how it can be used in predictive models in the study of future behavior [92]. Moreover, machine learning method has been applied in a study of projection of queuing behavior [84], [93]. The two research studies rely on a predictive modeling approach through their research has been defective regarding time series analysis on queue data prediction. In the multi-hospital study conducted by Dong et al [94], historical waiting times were analyzed and findings showed that ER waiting time is one of the elements patients consider when deciding where to seek treatment services.

The previously presented information is helping to make operational decisions that result in waiting time and overcrowding reduction in the ER [95]. Stintzing and Norrman [96] compared artificial neural networks (ANN) as a prediction method with optimization through queueing theory in companies to predict queueing behaviors. The authors claimed that the results from ANN were positive and could be used for predicting the right amount of service each day. Various predicting techniques have attempted in queue analysis to optimize the waiting time in the queue [97]; however, our model with multi optimization algorithms can be applied in evaluating the low acuity patient waiting times in the ER. Consequently, the proposed model in this study can be used to provide insights to ER medical staff to determine patient waiting time in the queue by using EHR data.

2.6. Patient Lab Test Results Prediction (COVID-19)

Several studies have attempted to propose models for COVID-19 prediction using different methodologies. For example, classification models and mathematical approaches have been implemented to predict COVID-19 symptoms based on patient hospitalization, death, and ICU beds [98], [99]. They have also been used to predict positive COVID-19 cases reported and the spread of the virus [100]. Similarly, Zivkovic et al. proposed hybrid machine learning algorithms method to predict new COVID-19 cases. They improved the current time-series forecasting of beetle antennae search (BAS) algorithm and the adaptive neuro-fuzzy inference system (ANFIS) machine learning method [101]. Moreover, a machine learning model proposed by [102] to predict COVID-19 diagnosis based on symptoms using data from Israel. Several features were used in this study to estimate the risk of infection such as sex, age and symptoms (Cough, Fever, Sore throat etc.)

A survey conducted for COVID-19 diagnostic test results across 50 states between July 10 and 26, 2020 found that the United States was not performing testing with nearly enough speed. The study results reported the mean waiting time of COVID-19 test results to be 4.1 days, with a median waiting time of about 3 days. Only 21% of sample people waited more than five days and 37% waited for within 2 days [103]. The average waiting time was 2.5 days per the data used in this research. Only 0.7% of the sample people waited for more than five days, and 74.4% waited for within 2.5 days. According to the authors in [103]the ideal time for test results should be returned within the same day.

Predictive models have long been used to understand and predict how diseases spread in populations [104], [105]. Machine learning (ML) techniques play a very critical role in yielding accurate predictions [106]. Aspects such as ML, reasoning, planning, and memory, among others, are part of the concept of Artificial Intelligence [107]. Predictive modeling, or predictive analytics, involves studying the creation of computer programs that learn and adapt when exposed to new data [108]. Observation or statistical data, for instance, is used to induce the algorithms, and subsequent optimization of their performance is the most common type of learning in ML.

Other examples of studies using ML approaches in the literature include predicting patient hospital admission [109], waiting time prediction and patient delay [82], predicting patient waiting time to be seen by doctor [86], predicting the mortality of patients diagnosed based on their sociodemographic and health information [110], and patient discharge time from hospital [111].

In other ML algorithm application areas, Artificial neural network (ANN) plays a critical role in the dynamic characteristics prediction, [112], studded the effect of delamination in laminated composite plate structures where the algorithms used to minimize the complex mathematical model and computational time. Similarity, Masanobu [113] used artificial neural network and support vector machines to predict the risk of bankruptcy for Japanese stock companies, including both the entire industry and individual accounts. Applying advanced ML and data driven techniques, Arun and Mallikarjuna [114] studied damage detection using a simple beam model to identify multiple structural damages using the signal or shape of the same damaged beam. The damaged procedure was identified using Wavelets and Local Regularity algorithms. Similarly, Mallikarjuna et al [115], proposed a new method to explain detecting structural damage for the beam and bridge modes of the spatial signals using empirical mode decomposition.

2.7. Machine Learning in Healthcare

Information technology advancements have made the use of machine learning possible in healthcare. One major breakthrough is the machine learning algorithm developed by Google that can identify cancerous tumors on mammograms [116]. Furthermore, Stanford University employs a deep learning algorithm to identify skin cancer [117], [118]. This deep machine-learning algorithm has also been found capable of diagnosing diabetic retinopathy in retinal images, as reported in an article by [119]. Accordingly, machine-learning technology has been a significant pointer towards accurate clinical decision-making. There exist differences in effectiveness in machine-learning techniques with a standardized machine being able to provide immediate and reproducible results [120]. Moreover, radiology and pathology algorithms with larger databases are also considered more effective.

Machine learning in healthcare can be trained on image identification, abnormality recognition, and point to areas which need attention, hence improving processes accuracy. Besides accuracy, machine learning can offer an objective opinion for efficiency, reliability, and accuracy of the process. Therefore, this technology will be beneficial to healthcare in long- and short-term applications [120]. For instance, it will assist family practitioners as well as interns while providing care to patients.

Machine learning will also significantly impact workflow to accelerate the clinical process and enhance financial outcomes. This is achieved by first reducing readmission through targeted, efficient, and patient-centered service delivery [121]. Technology helps clinicians to receive daily guidelines as to which patient is most likely to be readmitted, as well as give suggestions on how to reduce those risks.

Machine learning will also reduce the length of stay (LOS) by improving patient satisfaction and identifying patients likely to have an increased length of stay and suggest steps of best services to lessen the length of stay. The most significant benefit of machine learning is the ability to predict. With the ability to predict chronic diseases, it will help hospital systems identify patients with undiagnosed or misdiagnosed chronic disease, predict the likelihood of development of chronic disease in the patient, and present patient-specific prevention intervention [122], [123].

With the ability to predict a patient's health progress, machine learning will help reduce 1 – year mortality rate by predicting the likelihood of death within a year of discharge and then match patients with appropriate interventions, care providers, and support [100]. Moreover, with the predicting ability, machine learning will help predict the patient’s propensity to pay and recommend reminders, financial assistance, as well as establish the likelihood of payment changes over time and after particular events. Lastly, machine learning will also help the health systems to create accurate predictive models to assess with each scheduled appointment the risk of no-show hence improving patient care and the efficient use of the resource.

2.8. Machine Learning Solutions

Every year, new algorithms are developed to provide solutions to specific problems as researchers increasingly delve into topics related to machine learning and healthcare. Different papers such as; [124] done in Brazil, [125] in California, and [126] in China have been written, but all of them share a common goal of improving healthcare delivery. Chen shows that the many different papers implement their research findings on locally available data within the region, considering that some diseases manifest differently depending on areas [126]. Therefore, for most of the machine learning algorithms, it is a necessity to have training data to work on. The bigger the data, the more accurate the solution will be. The data can come from various sources (see Figure 2.1), and lately, the amount has increased quite fast [127].

Regarding data availability, some data can be publicly accessed, but others must be bought. The fact that some data can be accessed publicly suggests community support for the progress made. Conversely, more public data means that researchers with no access to a medical facility's data are forced to search, too. In healthcare, data comes from medical facilities in the form of medical records, but it can also come from other sources such as genomic data, internet usage, or mobile data. Internet usage, for instance, was used to predict epidemic outbreaks between 2008 and 2013 through Google Trends. Therefore, mobile data through any mobile device attached to the human body, such as a smartwatch, smart clothing, etc., can perform online evaluations in real-time given the recent developments in the IoT realm.

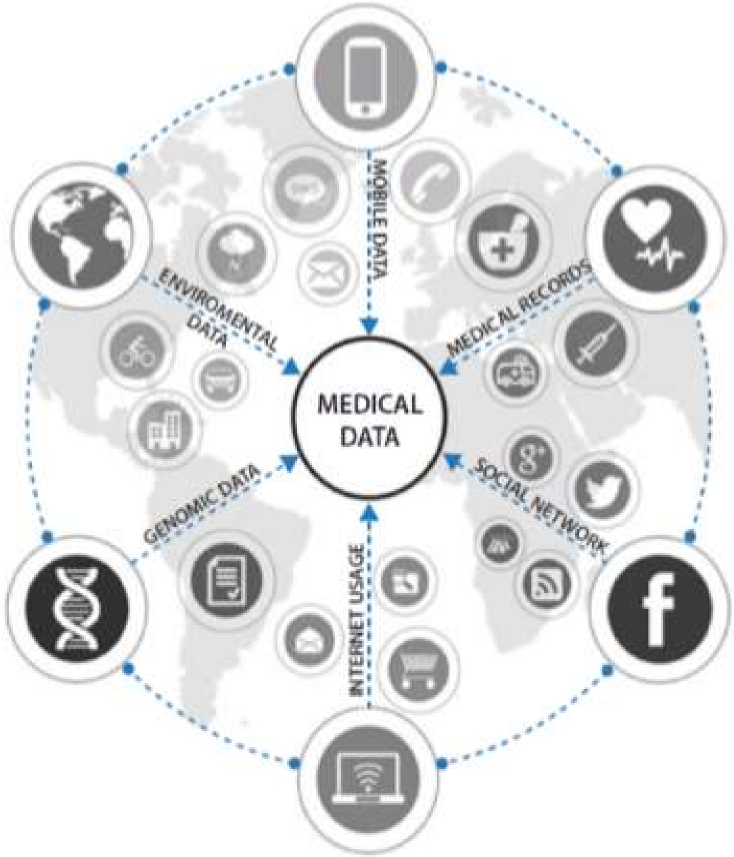

Figure 2.1. Sources of data in healthcare [127].

However, [128] suggests that optimization can be done to machine learning algorithms to allow the devices to perform more powerful processing while not running out of battery in a matter of minutes. The availability of required information presents a challenge for finding an appropriate algorithm capable of extracting only the useful information. The good news is machine learning is capable of such a task, according to recent research, although it is not yet 100 percent efficient. Nonetheless, machine learning sometimes outperforms human capabilities, providing a starting point for further research. Pollettini and Panico present that a machine learning system can be used in patients' classification on different Surveillance Levels (SLs); hence, a server Surveillance Level would mean that the patient requires immediate medical attention [124]. However, a patient's classification can be done with multiple machine learning algorithms, such as Relevant Feedback (RF), Artificial Neural Network (ANN), K-nearest Neighbor (KNN), and Decision Tree (DT). Das and Maharatna claim that accuracy is approximated to be about 87.81 percent. States that a machine learning algorithm can be used to identify people with chronic diseases such as cerebral infarction using data structured in age, sex, and smoking, among others, and unstructured data of text records of patients and or doctor's notes. One such algorithm is Convolutional Neural Network-based Multimodal Disease Risk Prediction (CNN-MDRP). The algorithm is a combination of CNN-based unimodal disease risk predictions that is used in extracting features from unstructured data, Naïve Bayesian (NB), KNN, and DT - used to extract features from structured data.

From such features in composition, the algorithm has an approximate 94.8 percent accuracy. According to Ghassemi, et all, of the algorithm, Recurrent Neural Network is capable of handling historical data [125]. Their algorithm can predict a patient's next diagnosis, medication, and visit time based on the person' previous records and the knowledge about all the patients. It is important to note that while the algorithm has an accuracy of about 78 percent, which is not good when compared to other algorithms, it is ultimately still better than the capabilities of the average doctor.

In the neuroscience branch of healthcare [129], learning machine algorithms can be used to determine patients with suicidal risks. Though some of the algorithms are more resistant than others, for instance, Support Vector Machine (SVM), ANN, and RF are more resistant as compared to BF Tree, as others are termed more vulnerable according to the author's experience.

2.9. Artificial Intelligence

On the verge of advancements in information technology, the term Artificial Intelligence (AI) has become common. AI is the study of creating intelligent machines and intelligent computer programs. Aspects such as machine learning (ML), reasoning, planning, and memory, among others, are part of the concept of AI [107]. Predictive modeling, or predictive analytics, involves the study of the creation of computer programs that learn and adapt when exposed to new data [108]. Observational or statistical data, for instance, is used for the induction of the algorithms, and subsequent optimization of their performance is the most common type of learning in ML. The three most common ML techniques are supervised learning, unsupervised learning, and reinforcement learning [130], [131].

One of the most critical subsets of artificial intelligence is Machine Learning, as it enables a machine to learn and act on individually identified tasks. By design, machine learning is made up of techniques and algorithms with the ability to predict upcoming events as well as do data classification through existing data pattern learning. Accordingly, essential algorithms in machine learning include; SVM, regression, Naïve Bayes algorithm, random forest, decision trees, deep learning, and gradient boosting [132].

One of the algorithms, logistic regression, helps to find linear model relations between variables by fitting a line on the curve of given data [133]. Moreover, logistic regression can be used in classification as applied in support vector machines algorithm [134]. The support vector machine has been attributed to the achievement of good generalization performance, hence the best data classifier for any given data.

On the other hand, decision tree tools for data modeling use a tree-like structure when classifying the decisions for data output classification. However, when many decision trees are used, random forest, an ensemble learning method, is produced [135]. Moreover, besides the decision trees and logistic regression, the gradient boosting method is also widely used in some machine learning problems [136]. Conversely, the gradient boosting method produces weaker models of an ensemble data model. However, the gradient boosting is commended for reducing biases and variance in the model.

In some sophisticated machine learning tasks, a deep learning algorithm has been successfully used. The deep learning algorithm is said to be another class of machine learning method, the ANN. Artificial neural network algorithms produce networks of cells with connections between those cells adjustable to learn the resulting structure of training data. However, there are higher layers in the network than in ordinary artificial neural networks hence enabling the algorithms to extract higher-level features from the input data. ANN is applied in many areas of studies to predict chaotic patterns, such as the flow of people through the queueing system, among other areas.

2.10. Artificial Neural Networks (ANNs)

In the human brain, billions of neurons are connected in such a way that it allows multiple interconnected communication flows. Artificial neural networks are mathematical models for machine control that are connected, and they work like the human brain. While no study has considered conducting a comparative analysis of the accuracy of ML methods against the traditional statistical methods, a number of studies have begun focusing on ML and, more specifically, on ANNs. Artificial neural network have received considerable attention because of their applicability in several fields, such as solving transportation problems [137]–[140], pattern recognitions, signal processing, system identification, and in the fields of medicine, economics

[141], [142], weather, market trend forecasting, mineral exploration, electrical and thermal load prediction, and adaptive robotics [137], [143], [144].

According to Zedah et al. (2005), ANNs are a class of nonlinear systems that can learn adaptively and perform tasks accomplishable by other systems, as well as be applied in a broad range of situations [145]. Such adaptability has been considered crucial by most researches [146]. The ANN modeling approach promises to replace the analytical difficulties encountered in other modeling approaches and computational algorithms [147]. Moreover, the ANN imitates the structure and mechanisms of the human brain, expanding its applicability, especially where the classical approaches have failed or proven too complicated to be adopted. ANNs are applied in the estimation of desired output parameters if adequate experimental data is provided. ANNs, therefore, allow the modeling of physical phenomena in a complex system without requiring explicit mathematical representation [146], [148]. Due to ANN not requiring prior knowledge of input data distribution, they have successfully proven to be universal approximators for unknown nonlinear multi-input and single-output (multi-output) functions. Despite the concept of ANN being in existence for almost half a century, it was not until two decades ago that software applications were developed to address practical problems, especially those involving incomplete data sets or highly complex and ill-defined issues that have been long decided based on human intuition [138], [142].

Artificial neural networks have also been effectively applied in the healthcare sector as one of the primary beneficiaries of the AI techniques. A survey of AI applications in health care reported that ANN uses in major disease areas such as cancer or cardiology [149]. An artificial neural network has been applicable in healthcare clinical diagnosis, especially concerning cancer prediction, speech recognition, image analysis, interpretation, and drug development, and in improving the patient workflow by prediction of the length of stay in hospitals [149].

Also, it has been applied in other non-clinical sectors, such as in the improvement of health care organizational management [150] as well as for predicting key indicators, such as cost or facility utilization [151]. Accordingly, ANNs have been beneficial to the effective decision-making process and in providing health care practitioners with time and cost-effective health care system solutions [152], [153]. Li and Zhou concluded that ANN is a useful tool for developing prediction models with high values for predicting cardiovascular autonomic (CA) dysfunction among the general population in China [154]. Among the successful areas where ANN has been applied in the recent past is in the diagnosis of chest diseases, such as lung cancer and asthma [155]. Moreover, there are other areas where ANN needs to be applied, especially in healthcare, such as queuing, and patients flow to help improve the potential services provision and effectiveness.

Several studies have focused on queuing system improvements, mainly how it can be used in a predictive model in the study of future behavior. Moreover, ANN is applied in a project of projection of queuing behavior [93]. On the other hand, Open Urban Data has been used as an accurate prediction of queue length in public service offices [96], therefore, relying on a predictive modeling approach through their research approach has been defective on time series analysis on queue data.

Additionally, some studies have been conducted to estimate the use of ANN in the prediction of time-series data and their predictions. However, Guresen applies expert systems with ANN model time-series data, especially in market data [156], arguing that the approach models stock market since it can quickly adapt to the market and does not have standard formulas. Satisfactory results were also realized by successfully predicting closing price using behavior tendencies through ANN [157]. Additionally, the Neural Networks were found to be better than the Statistical techniques in forecasting when compared through a comparative study [158]. Research on the performance ANN on time-series forecasting with QUICKPROP and RPROP, an improved version of the traditional Back Propagation algorithm, showed that the approach of modeling could be used in addressing real problems [159].

ANNs models have also been applied in the estimation of waiting-time as series data in banking queue systems. Some studies have also looked into the prediction of waiting-time in bank teller queues using different learning methods [160] conducted a study to predict the waiting time in bank teller queues using different learning methods. The authors developed and tested four prediction models using Gradient Boost Machine (GBM), Queueing Theory formula, Random Forest (RF), and Deep Learning (DL). Of the four models used, the Gradient Boost Machine proved most accurate, with 97 % accuracy and an F1 measure of 75 %. In addition, [96] used Queueing Theory formula with ANN to predict customer flow in stores where queuing is unavoidable.

Therefore, the study applies ANN in queue prediction and helps build the reliability of the use of multiple methods to construct data-driven prediction models, such as in the case of a study by [160]. Accordingly, one of the objectives of this study is to compare the effectiveness as well as the accuracy of different prediction methods. It also aims to investigate significant predictors of queueing time using ANNs. There are different architectures of artificial neural networks proposed in the literature (feed-forward, sequential, convolutional). More detail will be in the next section include ANN layers and structure of the neurons.

2.10.1. Architecture of an ANN

There are different architectures of artificial neural networks proposed in the literature (feed-forward, sequential, convolutional). The simplest form is a feed-forward neural network. Multilayered ANNs are divided into three major parts: input layer, hidden layer(s), and output layer, as shown in Figure 2.2. Why have single or multiple layers? This question should be the first concern before establishing the need for how many layers to specify. A single layer neural network is used only to represent linear and separable functions [161]. Accordingly, the single-layer neural network can be neatly separated by a line, as occurs in the instance of two classes with classification problems. The single-layer neural network is sufficient for a simple problem [107]. Multilayer Perceptron (MLP) can be used to represent convex regions. This means that, in effect, they can learn to draw shapes around examples in high-dimensional spaces that can separate and classify them, overcoming the limitation of linear separability.

The input layer contains information that is mapped to the output layer through the hidden layers. Therefore, each unit can only send its output to the units in the higher layer and receive its inputs from the lower layer. Accordingly, the number of nodes in the input and output layers are determined from the physics of the problem and equal to the numbers of input and output parameters, respectively [148]. The layers of neurons are interconnected by forwarding connections and made up of multilayer feedforward (MLF) neural networks. The chain of transformations that occur from input to output is known as the credit assignment path [162].

Information flow in the MLF network is organized in such a way that information is received from the neurons in the preceding layer before the data is processed using an internal model and passes the output to neurons in the succeeding layer. The structure of the neurons is simple: they consist of a summation operator, a local bias, and a nonlinear transfer function (activation functions). Their weight determines the strength of connections. The estimation of parameters (weights) is performed by minimizing a loss function (usually a quadratic function of the output error is used) [163].

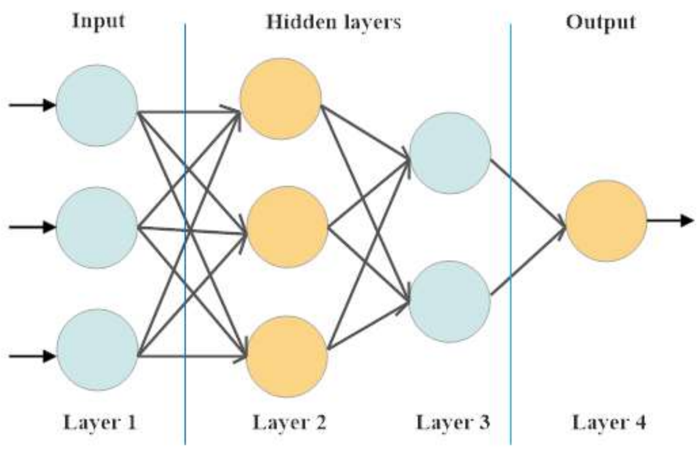

Figure 2.2. Architectures of neural network.

The elaborate layered structure and massive connections of the neuron network provide significant interaction among the processing elements, which enables them ot behave in a sophisticated manner collectively. Therefore, the ANN must be trained by a suitable algorithm of input and output data using classical experimentation networks such as back-propagation (BP) algorithm [164]. Since it is not easy to determine which algorithm will be fastest for any problem, a trial and error approach is used in testing the most effective and applicable algorithm [144]. According to Sha et al. (2004), Back-Propagation Neural networks (BPN) is widely used in prediction and pattern recognition, and they produce the best results. Rumelhart et al. (1986)

posit that the BP algorithm is the most widely used training procedure for MLF training [165]. The BP algorithm performs gradient description in an error space, provides a recursive formula for updating connection weights from an output layer, and works in reverse to the hidden first layer as well as in developing adaptive nonlinear controllers for complex systems.

Through experimentation the number of hidden layers, the numbers of neurons in each hidden layer, the type of transfer functions, and the number of training iterations are determined. The inputs and outputs of a neural network are determined by the application. Despite the progress made in the understanding of the basic behaviors of neural network systems, little is known about general rules for the selection of neural network topologies and parameters. Experimentation and exploitation of the special structure of a specific problem are often necessary for achieving the desired performance [166].

A feedforward ANN algorithm- multilayer perceptron (MLP) is used ambiguously or sometimes loosely and other times strictly to refer to a network composed of multiple layers of perceptron with threshold activation. This multilayer perceptron uses supervised learning techniques, such as backpropagation, for training [167]. The difference, however, between multilayer perceptron and linear perceptron is in the multilayer and non-linear activation. Accordingly, the MLP is used in distinguishing data that cannot be separated linearly [168].

For each training, Stochastic Gradient Descent (SGD) performs a parameter update because it is faster and better able to perform each update per time [169]. Accordingly, the algorithm is famous for training a wide range of models in machine learning [170] and includes linear support vector machines, as well as logistic regression and graphical models.

In 1988, Broomhead and Lowe proposed the Radial Basis Function Network (RBFN) model, which is based on conventional approximation techniques such as regularization techniques and generalized splines. The Radial Basis Function Network model is equal to MLP, but it is characterized as having faster training speed, and is therefore a better alternative to the MLP. By origin, the Radial Basis Function Network emanated from performing the exact interpolation of a set of data points in a multidimensional space [171].

The Radial Basis Function Network model has a similar structure as the classical regularization network [167] with basics of Green's function of the Gram's operator, which is associated with the stabilizer. However, RBF is only obtained when radial symmetry is shown. The approximation theory posits that the regulation network has three desirable properties [172], enabling it to proximate any multivariate continuous function on a compact domain to an arbitrary accuracy, if a sufficient number of units is provided. Accordingly, it is attributed to the best approximation property because of its unknown linear coefficients. This makes it minimize a functional regularization term, hence resulting in optimal solutions.

The above-mentioned methods of training algorithms fit output to input iteratively [173]. However, the method algorithms recommended for this research problem is the Levenberg-Marquardt algorithm [96], which is a combination of the Gauss-Newton algorithm and gradient descent algorithms that are utilized in solving nonlinear MSE problems. Accordingly, the algorithm adjusts the weights to reduce each stage error iteratively until it converges at some result. To add on that, after each training cycle, the algorithm uses a set of validation data or a set of inputs and corresponding outputs to produce comparable results, supposing the data were not used in training. Such an approach is used to avert overfitting, especially with changing weights, hence improving the results. Conversely, the training set results in worse outcomes than before on the validation set. Therefore, the final data set and the testing set are used after training to examine the performance of the ANN when predicting output in a given input [169].

CHAPTER THREE

APPLICATION OF MACHINE LEARING ALGORITHMS FOR PATIENT LENGTH OF STAY PREDICTION IN EMERGENCY DEPARTMENT DURING HAJJ

3.1. Introduction

In the hospital setting, the Emergency Department (ED), which offers timely emergency care for patients, is considered the busiest department, as providing care for the most urgent cases is essential [174]. Based on the nature of circumstances as urgent, the ED is characterized by uninterrupted serviceability.

The Annual Hajj pilgrimage event attracts millions of Muslims who visit the Holy Capital Mecca in Saudi Arabia. The ritual is often held in the last month of the Islamic year, between 8 and 13 DhulHijjah. This ritual is a significant celebration in the Islamic religion and hence attracts people from around the world who converge in Mecca. Excessive overcrowding exists in ED across the city during this period, in Al-Mashaer hospitals for example, due to stochastic arrivals and different patient health conditions, such as patients over 65 years of age. According to Mirza et al. [175], length of stay (LOS) is affected by the patient's characteristics (e.g., age and mode of arrival) in EDs. This study investigates a single variable, patients' LOS, as a major issue reported by the hospitals which may affect overcrowding.

In general, people with less urgent care are attended to in different departments; the ED remains the most overcrowded section in the hospital, hence resulting in longer waiting times and lower satisfaction levels among visiting patients as complex conditions may occur [3]. According to a study aimed at evaluating the operations and quality of care at EDs, average wait time, the average LOS, resource utilization, ED productivity, and layout efficiency are all factors to consider [176]. In [175] the author outlined determinants linked to longer waiting times by the mode of admission, admission period, admitting department, number of comorbidities, and intensive care unit (ICU) admissions. Moreover, long waits in triage, delays experienced in testing and waiting for test results, waiting for physicians, and a shortage of nursing staff all contribute to a prolonged wait times in the ED [177].

According to El-Sharo [178] inefficient utilization of ED resources, delays in patient admission in ED, and miscommunication between ED staff hampers an efficient flow of patients in and out of the ED. In addition, inefficient allocation of resources in the hospital, as well as external factors such as insufficient primary care facilities in the neighborhood that results in increased patient demand, are also factors that lead to longer waiting times in the ED. Therefore, hospital ED costs and effectiveness are assessed using LOS by employing several forecasting methods [73].

3.2. Methodology

The proposed methodological framework is based on predictive modeling to approximate the length of stay of Hajj patients in the ED. The goal is to enable prediction models with the available data and make it easily understandable and usable. The methodology adopted to achieve this research is outlined in Figure 3.1. Each step is described in the following subsections. The first step is the data description which shows where and how the data was applied. The second step is a statistical summary, which shows the inputs variables used in the model. The third step is data rescaling, and it shows how the data transform from existing categories to binary numbers. Features selection is described as the fourth step in this study, and the prediction processes and the algorithms used are indicated in the last step.

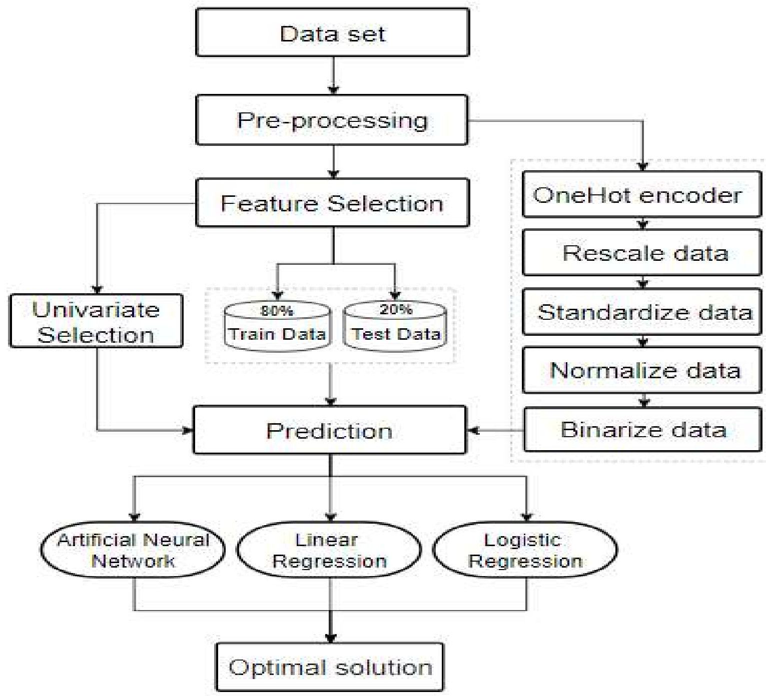

Figure 3.1. Proposed methodology for LOS prediction.

3.2.1. Dataset Description

The data was obtained from a research paper published in 2018 and collected between the 16th day of Dhu al-Qidah and the fourth day of Muharram, corresponding to 31 August–17 October [175], from a public hospital emergency department in Mecca, Saudi Arabia, that serves an average of 150,000 patients per year. The total data collected was 296 ED patients admitted during the peak Hajj period. The Hajj season was divided into three consecutive periods: the pre-ritual period before the 8th day of Dhu al-Hijjah (21 days), the peak Hajj period between the 8–13th days of Dhu al-Hijjah (6 days), and the post-ritual period after the 13th day of Dhu al-Hijjah (21 days). The data has been expanded (734 ED patients) and during the preparation, we assumed that we have three hospitals with total 2202 patients. The methodology adopted to achieve this expansion is shown in Figure 3.2.

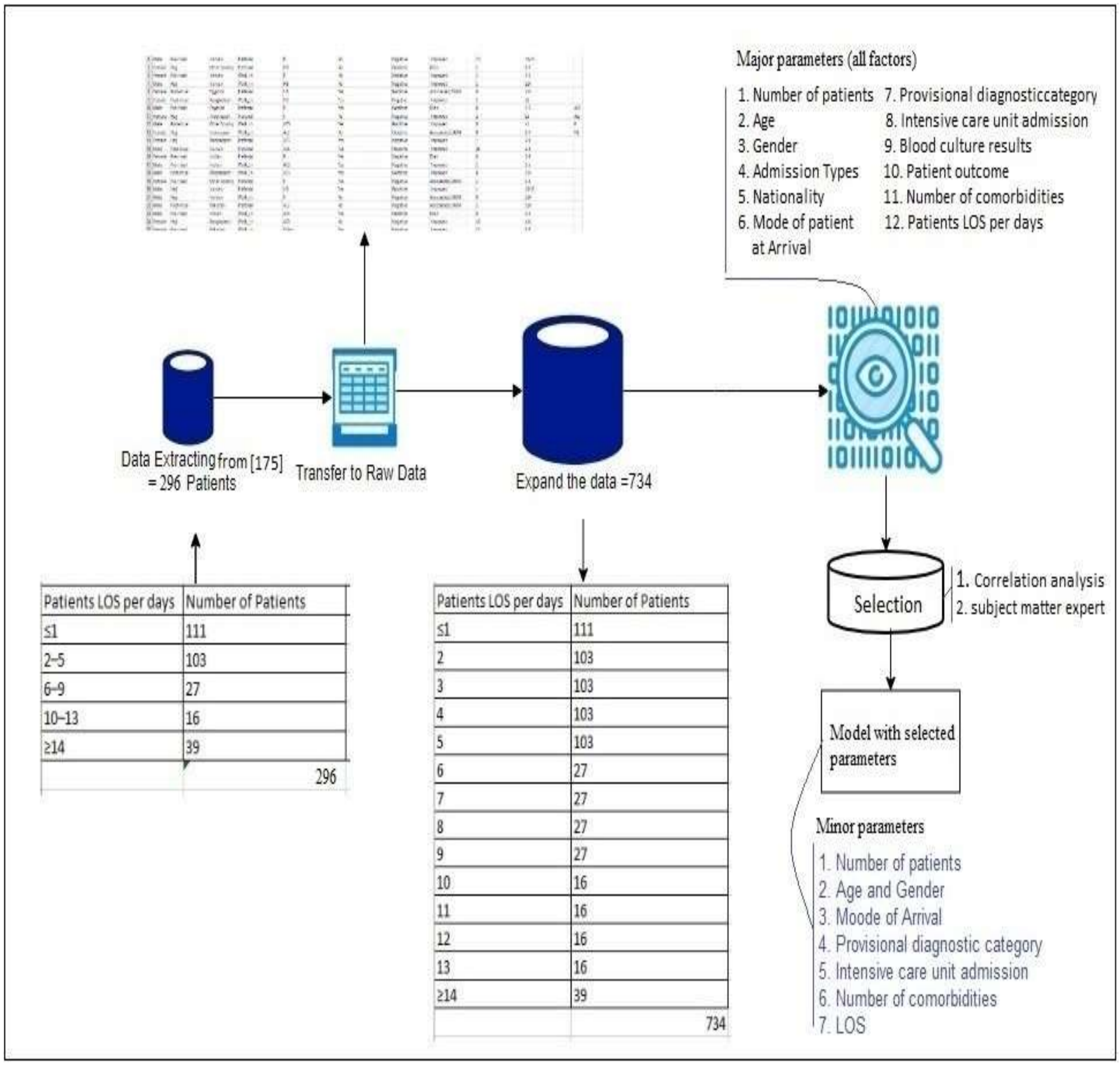

Figure 3.2. Proposed data expanding and the factors extracting methodology.

3.2.2. Statistical Summary

The data was used for generating a model are summarized in the statistical results presented in Tables I. The original data includes factors such as gender, age, mode of arrival, number of comorbidities, ICU admission, provisional diagnostic category, admission period, nationality, blood culture results, and patient outcome. Only some, not all factors, of the original data have been used in the alternative model (Table 3.1) and presented in this research.

Table 3.1. Summarized of statically results variables. (ACS_Acute coronary syndrome, ALC_ Altered level of consciousness, P_ Pulmonary oedema, HB_Heart blockage).

Factors	Factor Type	Description	Number of Patients Recorded	%
Gender	Input	Male	218	73.6
		Female	78	26.4
Age in years	Input	23–34	4	1.4
		35–44	15	5.1
		45–54	49	16.6
		55–64	116	39.2
		65–74	79	26.7
		75–84	30	10.1
Mode of patient at arrival	Input	Walk In	115	38.9
		Referral	181	61.1
Number of comorbidities	Input	None comorbidities	49	16.6
		One comorbidity	72	24.3
		Two or more comorbidities	67	22.6
Intensive care unit admission	Input	Yes	118	39.9
		No	178	60.1
Provisional diagnostic category	Input	ACS	193	65.2
		ALC	42	14.2
		P	16	5.4
		HB	15	5.1
		other	30	10.1

The statistical summary table above shows factors, factors type (the input factor to the model), the factors description such as gender (male and female), and the number of patients recorded with its percentage.

3.2.3. Data Rescaling

The proposed dataset comprised age, gender, mode of arrival, etc. The data considered the major and minor parameters from our dataset. In the preprocessing step, a hot encoder was used to encode the categorical or text data into binary data (into numbers) which required further analysis for machine learning process. The converter array structure can be shown in Figures 3-5 below.

```
[[1.    0.    0.    1.    1.   ]
 [1.    1.    1.    0.    0.   ]
 [1.    0.    1.    0.    0.667]
 [1.    1.    1.    0.    1.   ]
 [0.    1.    0.6   1.    0.333]]
```

Figure 3.3. Rescaling all the values in the range between 0 and 1.

```
[[0.516 0.258 0.    0.258 0.775]
 [0.348 0.348 0.87  0.    0.   ]
 [0.343 0.171 0.857 0.    0.343]
 [0.309 0.309 0.772 0.    0.463]
 [0.25  0.5   0.75  0.25  0.25 ]]
```

Figure 3.4. The rows are normalized to length 1.

```
[[ 0.971 -1.    -1.463  1.059  1.304]
 [ 0.971  1.     1.463 -0.944 -1.332]
 [ 0.971 -1.     1.463 -0.944  0.425]
 [ 0.971  1.     1.463 -0.944  1.304]
 [-1.029  1.     0.292  1.059 -0.454]]
```

Figure 3.5. Values for each attribute have a mean value of 0 and a standard deviation of 1.

The dataset split into a training and testing set by 80 percent to train the algorithms and 20 percent to predictions and evaluate the prediction against the expected results. The predicted output and the model accuracy were presented in results. Neural networks, linear and logistic regression are used to classify and predict our data.

<u>3.2.4. Feature Selection</u>

There was an argument regarding which factors should be used in the model. Two methods were used for factor selection, the expert opinion and correlation analysis (univariate selection) [179], after discussing with doctors (subject matter experts) who experienced the patients' LOS in Saud Arabia during the Hajj event. The factors are divided into two types: high and low effect on LOS. The factors with low effect on the LOS, such as admission period, nationality, blood culture results, and patient outcome, were eliminated from the training set in the alternative model. The remaining factors that have more focus on our training set, such as age (high affect), gender (median effect), mode of the patient at arrival (high affect), provisional diagnostic category (median effect), ICU admission (median effect), and number of comorbidities (high affect), were included. Also, correlation analysis was used to increase the accuracy of factor selection and support expert opinion. The alternative model includes factors with a high and medium correlation. The correlation analysis is performed by Minitab® 19, with a significance level (α) of 0.05. The correlation coefficient calculated for every factor with LOS. The results are shown in Table 3.2. The significance divided into three correlation strengths as in [1]: strong (1-p>0.95), medium (0.90<1-p<0.95), and weak (1-p<0.90), where *p* is the test probability value. Most of the strong factors have high effect as raised by the subject matter experts.

Table 3.2. Correlation of all variables.

Factors	Correlation coefficient	P-value	Correlation
Age	0.208	0.000	Strong
Number of comorbidities	-0.010	0.000	Strong
Gender	-0.040	0.089	Medium
Admission period	0.048	0.195	Weak
Nationality	-0.010	0.793	Weak
Mode of patient at Arrival	0.013	0.000	Strong
Provisional diagnostic category	-0.014	0.099	Medium
Intensive care unit admission	-0.014	0.000	Strong
Blood culture results	-0.104	0.715	Weak

3.2.5. LOS Prediction

Different libraries in Python 3.7, were used to build a code to import, prepare, and predict the Hajj patients' dataset. The libraries use LR, and classification include numpy, matplotlib, and pandas to import the data set and prepare it for the training. With regards to rescaling the data set (all attributes have the same scale between 0 and 1), the scikit-learn using the MinMaxScaler function was used. Also, the sklearn.liner_model function was used to train, test, and split the data. Moreover, it was used to calculate r^2 (R Squared). It provides a suggestion of the goodness of fit of a set of predictions to the actual values. In classification regression, the sklearn.metrics function was used to import confusion matrix. The confusion matrix represents the examples in a predicted class, while each column represents the instances in an actual class.

3.3. Results and Discussion

Different machine learning algorithms were used, including neural networks, linear and classification regression. The model was used major parameters (all factors for model) and then minor parameters (selected factors for alternative model) to train the dataset. The results and the accuracy of the training models are in following sections.

3.3.1. Artificial Neural Networks Algorithm

Multi-layer Backend was used in ANN with input parameters. For training of network, different functions were used, such as crossentropy from Keras, and logarithmic loss to search through different weights for the network and any optional metrics. The learning algorithm used in this model is gradient descent with six inputs factors. We ran the model in different iterations and the best network structure found for the model was through a process of trial-and-error experimentation. The accuracy of the best model is 78.29 shown in Figure 3.6. The networks architectures were 6 inputs (visible layer), 32 neurons (hidden layer), 18 neurons in the next hidden layer and one output in the output layer as shown in the summary of the ANN model in Table 3.3.

Table 3.3. The summary of best model resulted.

Summary of the ANN model	
Network Architecture	[32-18-1]
Training Algorithm	Gradient descent algorithm
Number of Iterations	500
Accuracy	78.29

```
2202/2202 [==============================] - 0s 85us/step - loss: 0.4826 - acc: 0.7607
Epoch 491/500
2202/2202 [==============================] - 0s 78us/step - loss: 0.4776 - acc: 0.7652
Epoch 492/500
2202/2202 [==============================] - 0s 71us/step - loss: 0.4742 - acc: 0.7661
Epoch 493/500
2202/2202 [==============================] - 0s 71us/step - loss: 0.4775 - acc: 0.7593
Epoch 494/500
2202/2202 [==============================] - 0s 71us/step - loss: 0.4811 - acc: 0.7648
Epoch 495/500
2202/2202 [==============================] - 0s 92us/step - loss: 0.4805 - acc: 0.7620
Epoch 496/500
2202/2202 [==============================] - 0s 92us/step - loss: 0.4758 - acc: 0.7684
Epoch 497/500
2202/2202 [==============================] - 0s 78us/step - loss: 0.4755 - acc: 0.7702
Epoch 498/500
2202/2202 [==============================] - 0s 85us/step - loss: 0.4764 - acc: 0.7602
Epoch 499/500
2202/2202 [==============================] - 0s 78us/step - loss: 0.4739 - acc: 0.7629
Epoch 500/500
2202/2202 [==============================] - 0s 78us/step - loss: 0.4764 - acc: 0.7666
2202/2202 [==============================] - 0s 163us/step
Accuracy: 78.29
```

Figure 3.6. Training neural network results for patients LOS.

Figure. 3.7. It shows the model accuracy (acc) on train and validation datasets. It can be clear the trend for accuracy on both datasets is still rising for the last few epochs which mean that the model could probably be trained a little more. In addition, the model has not yet over learned the training dataset, and it shows the comparable skill on both train and validation datasets.

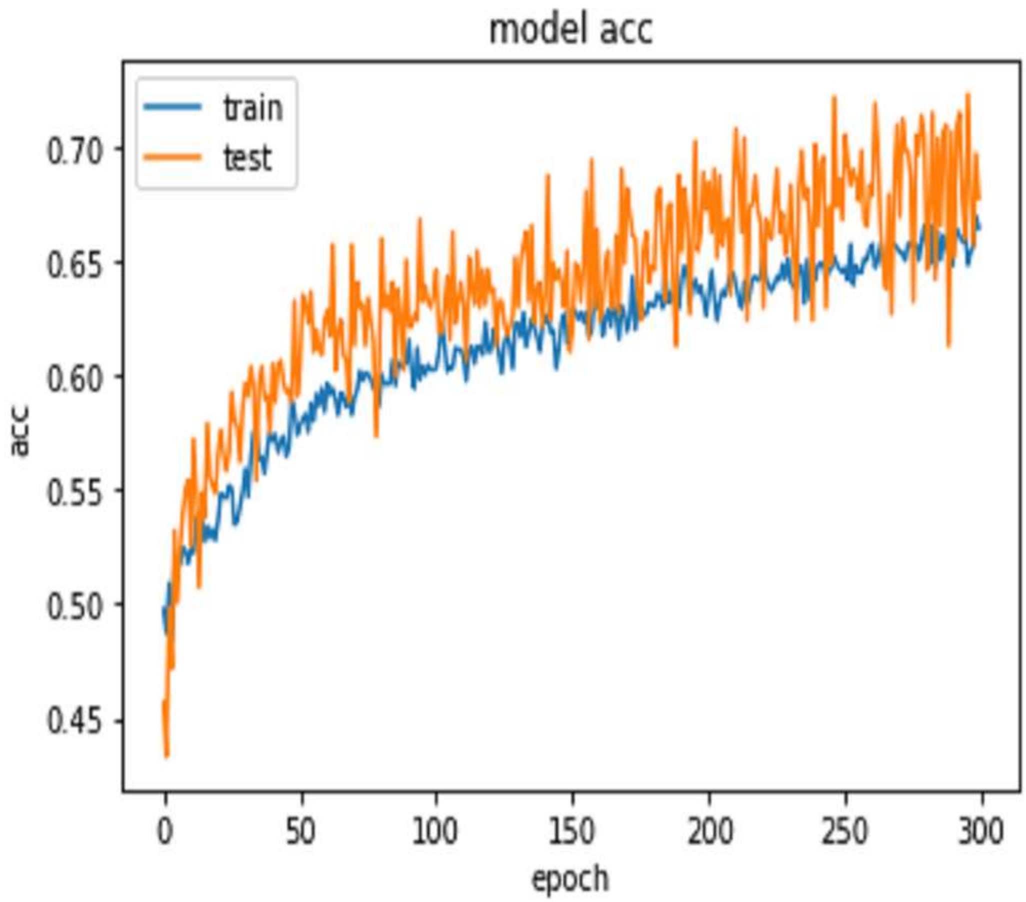

Figure 3.7. Plot of model accuracy on train and validation datasets.

Figure 3. 8. It shows the model loss on both datasets. It’s clear that on the plot of loss, the model has comparable performance on both train and validation datasets. It might be use as a sign to stop training at an earlier epoch if these parallel plots start to depart consistently. It could learn a lot about neural networks and deep learning models by observing their performance over time during training.

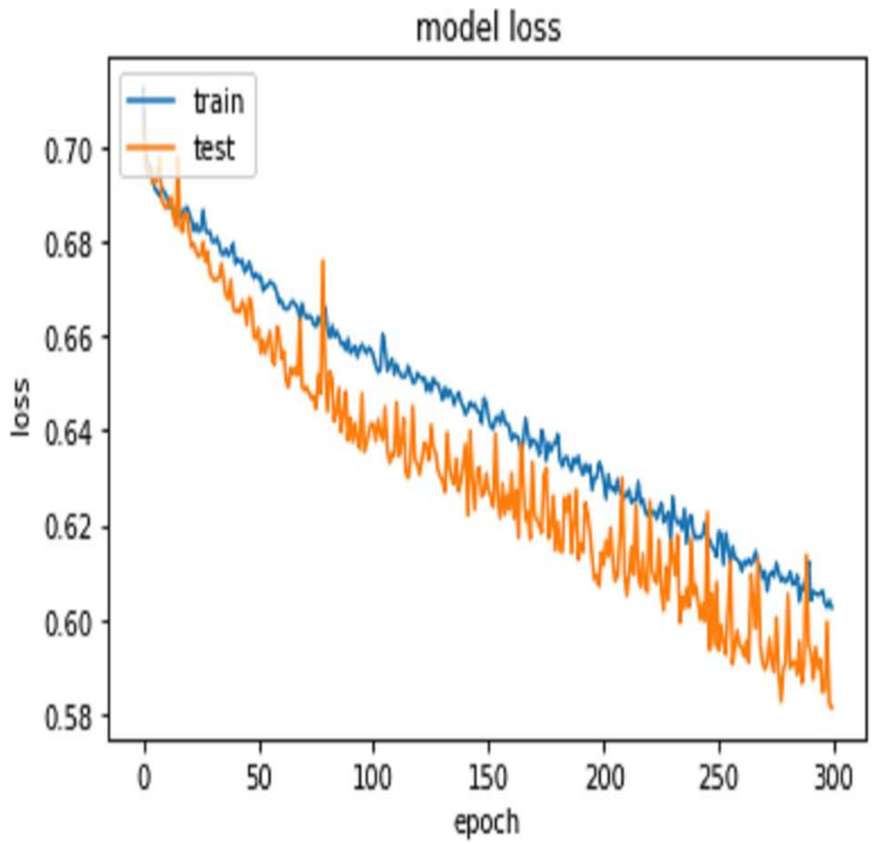

Figure 3.8. Plot of model loss on training and validation datasets.

In the previous plots, the performance of the deep learning model was reviewed and visualized over time during training. One of the default is the callbacks, that is registered when training all deep learning models is the History callback. It records training metrics for each epoch, which includes the loss and the accuracy.

3.3.2. Linear Regression Algorithm

The following figures, Figure 3. 9. (a&b), shows the Hajj patients prediction length of stay with selected factors such as age and gender. Figure 3.9. (a) shows the relationship of the patient ages with length of stay. We can see that elderly patients have higher length of stay from 49 to 80 years of age.

Figure 3. 9. (b) represent the number of patients with their length of stay versus the gender, it is clear that the majority of both male and female patients stay at emergency between ≤1 day to 15 days. A few patients stayed more than 15 days; most of them were elderly as shown in the figures right side.

According to the graph from linear regression, the relationship between age and length of stay is direct when the age increased. The length of stay increased too, and the accuracy of the trained linear regression with overall is about 72 percent.

The mode of arrival is shown in Figure 3. 10 (a), the LOS for referred is higher than walk-in. If we compare this Figure 3. 10. (a) with Figure 3. 9 (a&b), it clear that most of the patients who stay longer are female referred from other facilities and around 48 to 54 years old.

Figure 3. 10. (b) shows the number of comorbidities, which presented as zero refer to no comorbidities recorded during patient stay; 1 refers to patients with only one comorbidity; 2 refers to patient with more than one or three comorbidities, 3 refers to if the patient has more than three comorbidities.

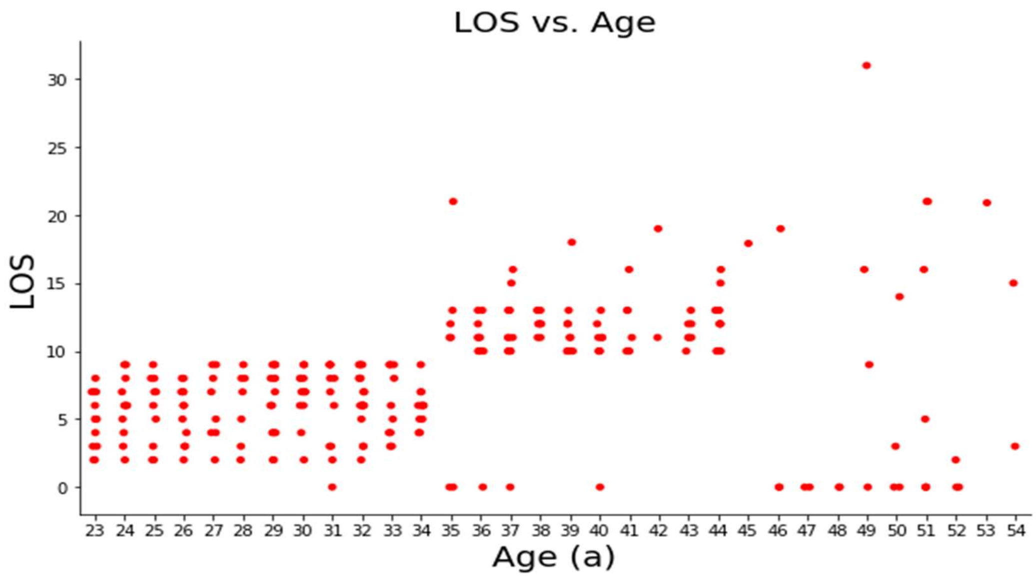

Figure 3.9 (a). Prediction of Hajj patient length of stay with age.

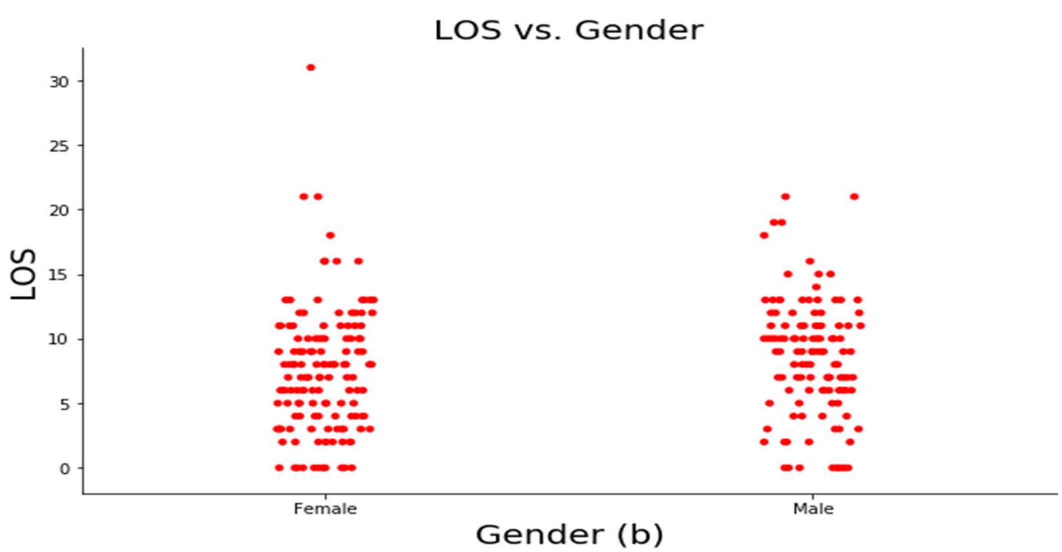

Figure 3.9 (b). Prediction of Hajj patient length of stay with gender.

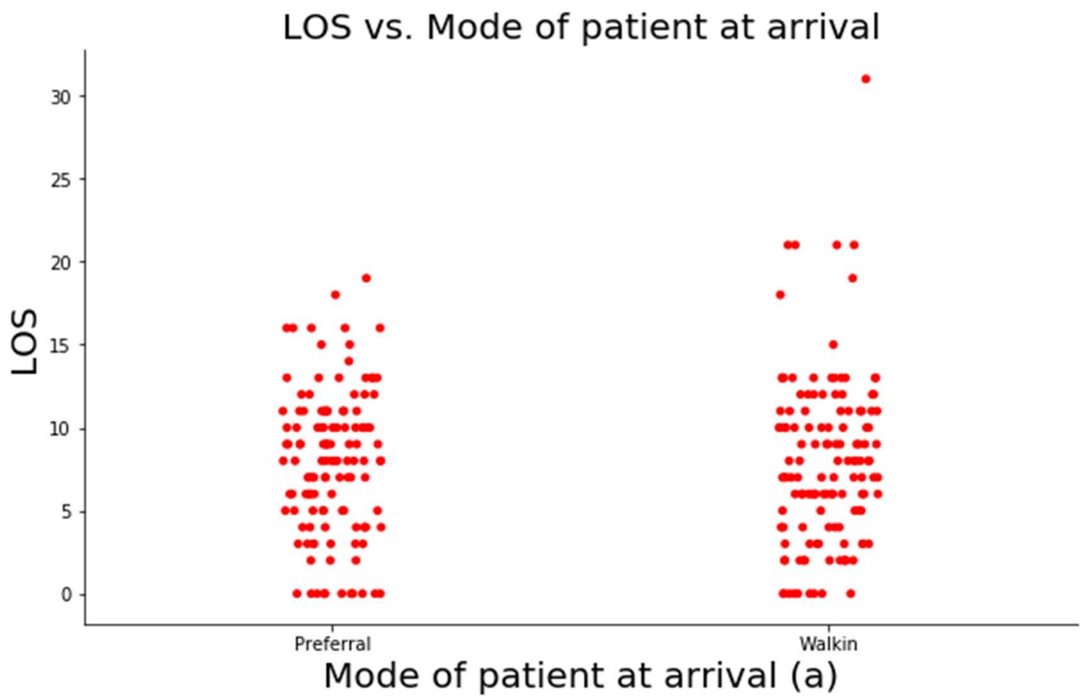

Figure 3.10 (a). Prediction of Hajj patient length of stay with mode of arrival.

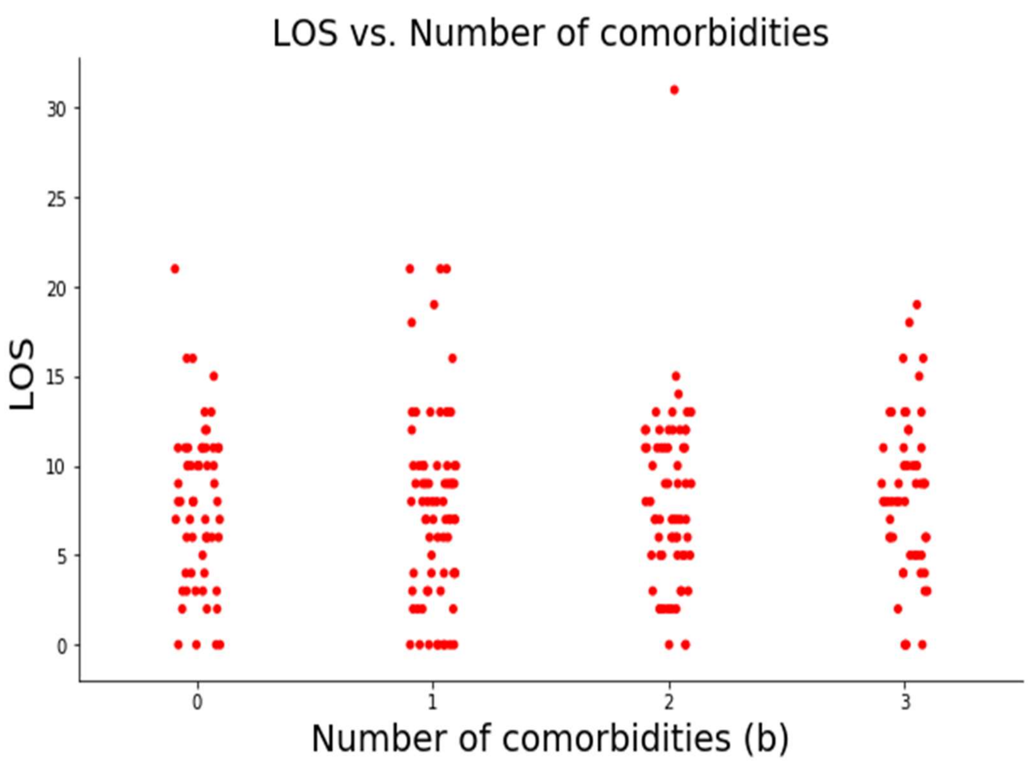

Figure 3.10 (b). Prediction of Hajj patient length of stay with number of comorbidities.

Figure 3. 11. (a) presents the results of a provisional diagnostic category associated with LOS such as acute coronary syndrome (ACS), altered level of consciousness (ALS), heart blockage (HB), pulmonary oedema (P) and others. The most patient LOS with provisional diagnosis was ACS. Figure 3. 11. (b), presents the results of intensive care unit (ICU). According to the graphs a & b, the majority of the patients were need intensive care and they stay for long time at ED.

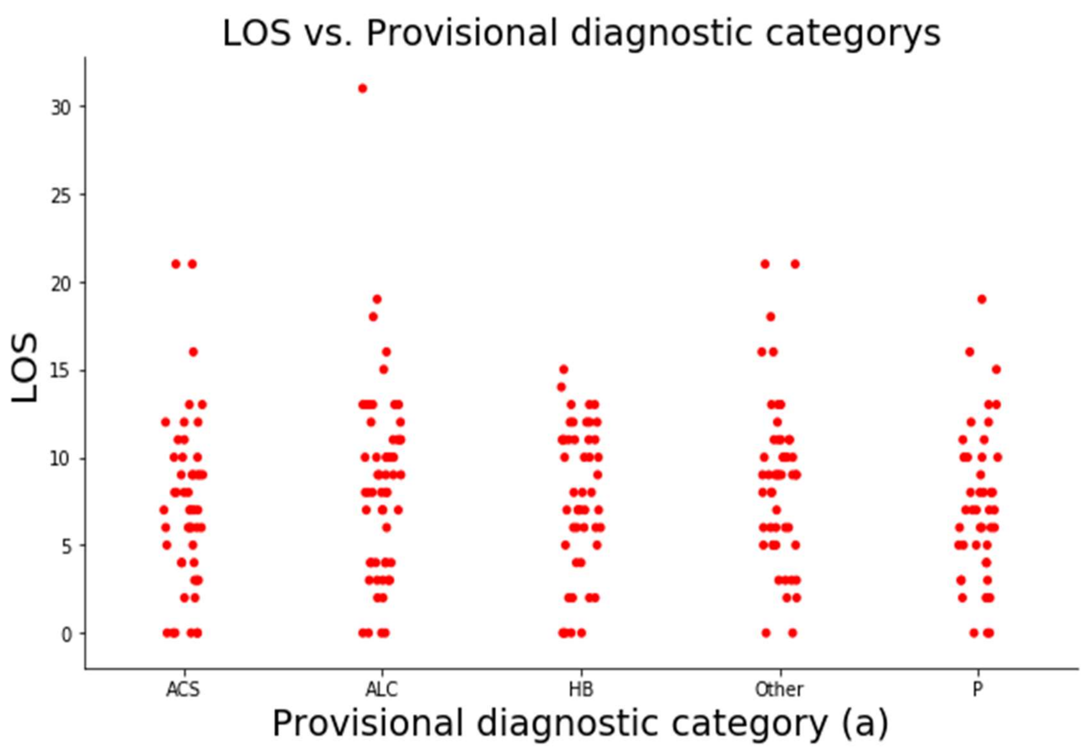

Figure 3.11 (a). Prediction of Hajj patient length of stay with provisional diagnostic category.

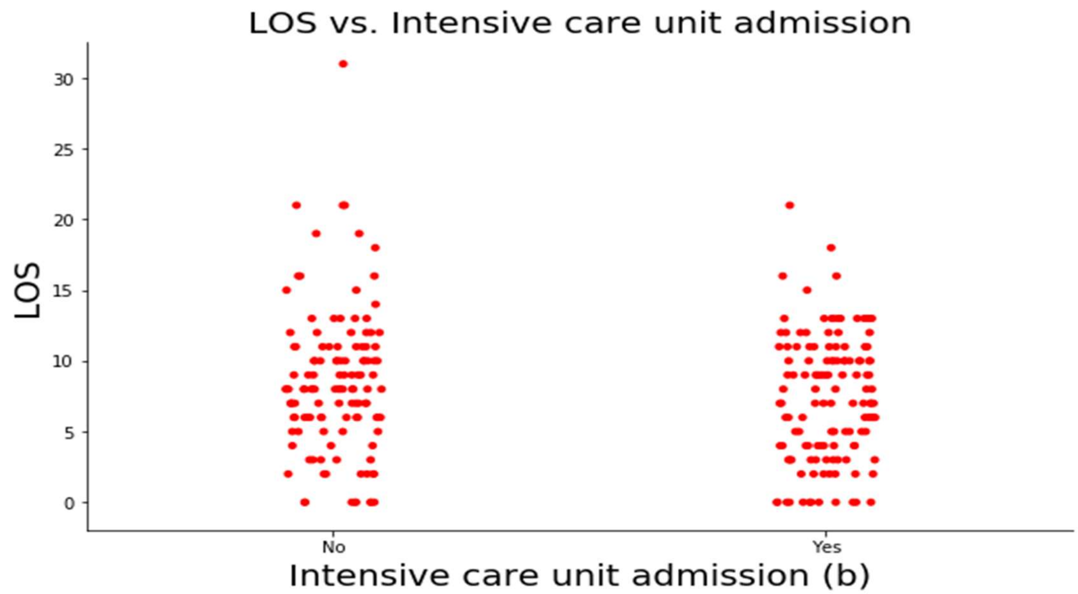

Figure 3.11 (b). Prediction of Hajj patient length of stay with ICU.

3.3.3. Logistic Regression Algorithm

In the logistic regression, the dataset was split into a training set and testing set by 20 and 80 percent, using sklearn.model_selection function. In the confusion matrix (error matrix) below, the layout is a summary of the prediction results, visualization of the performance algorithms and the overall accuracy is about 50 percent, as shown in Figure 3. 12. It predicts as a yes or no (either Patient has LOS or not). The major factor contribution is the ninth parameter.

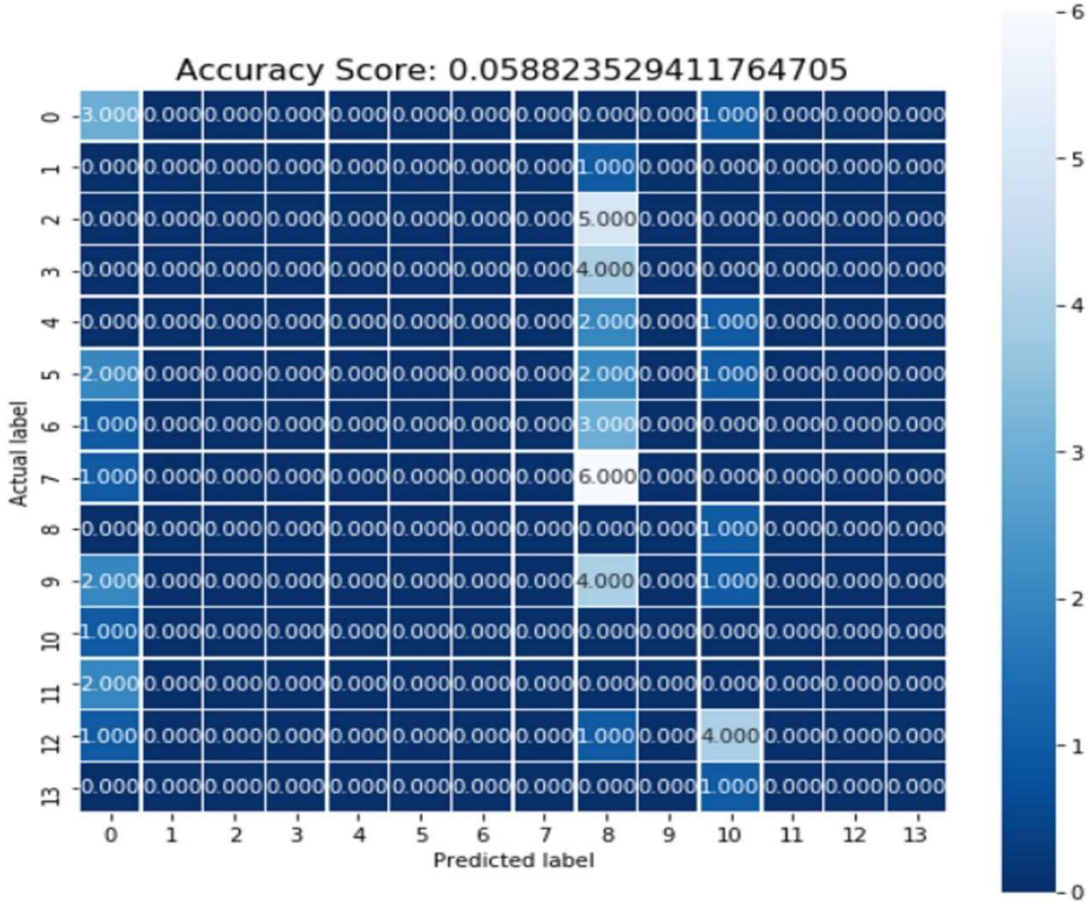

Figure 3.12. Confusion matrix of actual and predicted label.

3.4. Conclusion

This chapter presents a prediction model for Hajj patients' LOS using Machine learning algorithms. The available data for 2202 patients were analyzed which represented the original 296 patients observed during the Hajj event. The proposed dataset comprised of age, gender, mode of arrival, etc. We considered the data with major and minor parameters from our dataset. While most of the data factors are categorical variables, in a preprocessing step, we used the hot encoder to encode the categorical data to the binary data. In the research, we proposed artificial neural networks, linear and logistic regression-based models that included all factors and an alternative model that took into consideration selected factors except factors with a weak correlation with LOS. The modeling result, prediction accuracy for ANN was 78.29 percent, and overall, for linear regression was 72 and 50 percent for the logistic regression model[1].

[1] H. Hijry and R. Olawoyin, "Application of Machine Learning Algorithms for Patient Length of Stay Prediction in Emergency Department During Hajj," *2020 IEEE International Conference on Prognostics and Health Management (ICPHM)*, 2020, pp. 1-8, doi: 10.1109/ICPHM49022.2020.9187055

CHAPTER FOUR

PREDICTING PATIENT WAITING TIME IN QUEUING SYSTEM USING DEEP LEARNING ALGORITHMS IN THE EMERGENCY ROOM

4.1. Introduction

Emergency rooms (ER) experience massive patient overcrowding at most hospitals because more than 50% of the patients who are admitted to the hospital come through the ER. The ER is a valuable part of hospitals, and as such, most sections require many resources due to long patient queues [180]. In a setting such as healthcare, queueing is a risk factor because idle time can prove to be expensive for healthcare providers and unpleasant for patients. Moreover, it may also affect a patient's health conditions or life [181]. Queuing theory (QT) is a traditional mathematical technique that has been used to analyze queuing systems for decades [182]. However, the traditional QT approach may not be sufficient in real life applications because the methodology is limited, for example, unrealistic assumptions of the time distribution it requires to do queueing analysis [183], [184]. Thus, alternative techniques, such as deep learning (DL) algorithms, are considered to significantly improve ER efficiency. DL algorithms are another class of machine learning method. Also, recent research reported that the methodology applied to predict the patient waiting time at ER has limited accuracy [86]. Furthermore, DL algorithms can reduce human error and have even better accuracy compared with traditional methods [185]. The goal of this study was to deliver a novel and more accurate model for waiting time prediction and make an essential tool for reactive actions if ERs report long waiting times. This goal was motivated by high error rates in previous studies. The novel model produced in this study reduces error prediction compared to prior work on this topic.

From an applied perspective, a new algorithm was developed with DL to improve waiting time prediction accuracy for patients with low acuity using queueing predictor variables at the ER. The DL method was compared with traditional mathematical approaches. Realistic data was utilized from the triage monitoring system at an ER in Saudi Arabia which contained 30,909 patients between January and December of 2018.

Current studies have developed associations between the length of waiting time and the level of customer dissatisfaction [186]. Hence, they are encouraged to consider achieving adequate resource allocation to minimize waiting time in queues. Healthcare is one sector that is required to improve customer service in order to improve overall satisfaction and positive health outcomes. Extreme waiting times lead to poorer healthcare outcomes and are used as a measure of access to healthcare facilities [187].

There are typically different techniques (e.g., mathematical analysis) to optimize queueing and resource utilization [188]. For example, queue models are frequently used to handle high demand by evaluating waiting times in hospital pharmacies and other multiple points of services. Similarly, other service industries that require security control, such as airports, also employ queueing models [186]. Moreover, waiting time in the queue is considered a measure of traffic control strategy performance. For instance, queuing delay is responsible for more than 90% of delays in travel time and traffic congestion at the airport[189]. Queuing models are also applicable in daily life where people wait in grocery stores or in restaurants for food. Studies have suggested that longer waiting times in any system may lead to higher consumption [94], [190]. When queues move slowly, it increases the waiting time and prominence thereof, and in turn requires the usage of more resources.

4.2. Methodology

Deep learning techniques are implemented in this study to predict patient waiting time in queueing system alongside, or in place of, queueing theory (QT) using EHR data. Next, we compare the DL algorithms to find the best model with the lowest MAE. The model is presented, and a flowchart of the proposed methodology is shown in Figure 4.1. Each step is illustrated in the following subsections.

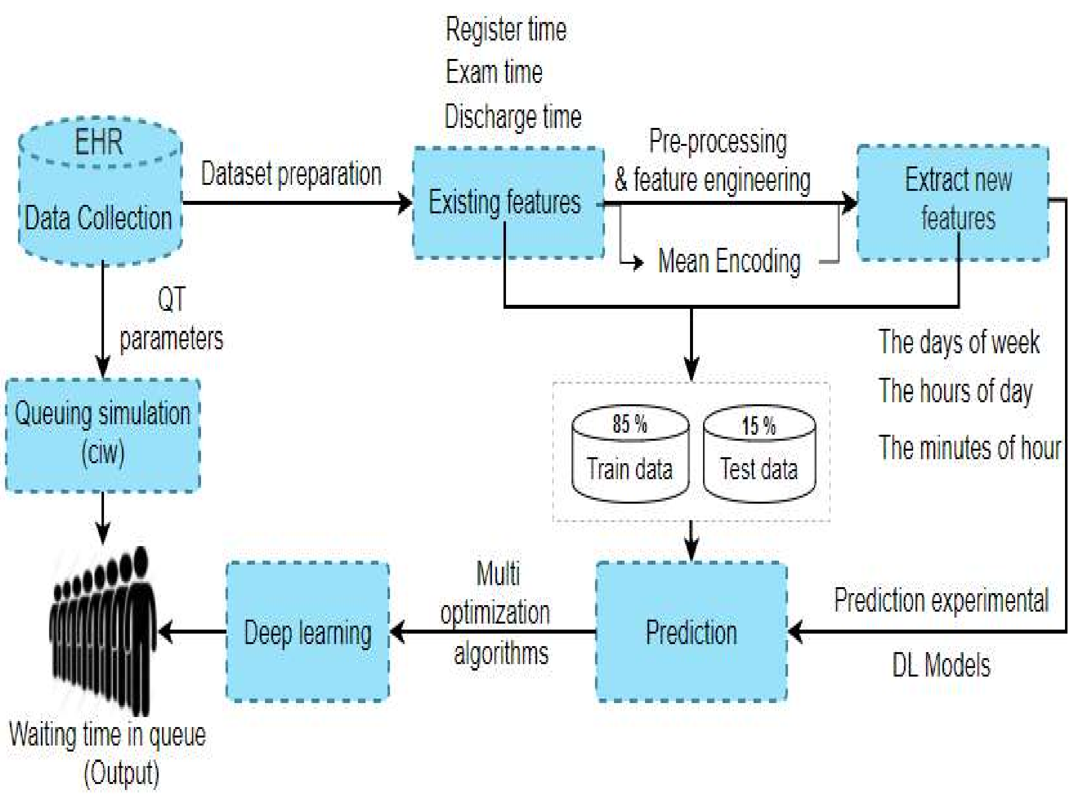

Figure 4.1. Proposed methodology for waiting time prediction.

4.2.1. Data Description and Preparation

The Triage Monitoring system is a national database established by the Ministry of Health of Saudi Arabia to ensure patient care quality. The data was extracted from the Triage Monitoring system, which includes data related to the formation and service of queues in hospitals at an ER between January and December of 2018. It recorded and monitored the patient flow time from when they registered until they left the hospital. These are the key referents for the application of machine learning, especially in the prediction of a new patient's waiting time upon joining a queue. These data included time of checking into the queue (arrival time/registration time), time taken in the queue (waiting time), time taken at server point (service time/exam by doctor), and sum of time taken in the entire system processes (length of stay).

The main data extracted from the EHR were entered randomly. Multiple steps were undertaken to clean, analyze, and finalize the data: **Step 1**, we converted our data using the arrival time/register time into weeks. **Step 2** used Step 1 data to create daily data. **Step 3**, the data were sorted based on arrival time to make the entries in a sequence of arrival. **Step 4**, missing and high values (manual data entered errors) in the data were excluded from our analysis. **Step 5** included only patients with level 3 through 5 acuities because more than 70% of the data that we collected included these types, which contained around 30,909 patients who were used in the training model after data cleaning. Also, irrelevant features, such as patient ID and names, were removed from the dataset.

The dataset reported one server (examination by doctor); hence, the triage service time was merged with waiting time (for time from arrival to first time being seen by doctor). Patients with these levels are considered less urgent or non-urgent. These types of patients do not need immediate care and are usually treated as first come first served. Therefore, the output variable in this model is the waiting time that the machine learning algorithms seek to predict. The mean waiting time in the dataset was 44.76 minutes, 39.0 minutes for median, and 20.23minutes as standard deviation. Different input variables were analyzed, including service time, waiting time, and people waiting versus days of the week to give initial insights of our model data. The service time in our data is the time when the patient started getting treated by a physician until the treatment ended. Dataset (new features extracted) is used in this case to calculate patients in the queue and for every patient when they join the queue.

To calculate the sum of people in the queue, every time patients departed from the queue, we found the sum of the waiting time and the arrival time before counting the number of people still in the queue when a new patient joined the queue. In machine learning, feature selection and data preparation are commonly used methods.

In machine learning, feature selection and data preparation are commonly used methods. Also, exploratory data analysis and the correlation check process are important parts. The more natural way to understand the data is by visualization. Heatmaps can be used to visualize correlation matrices.

Different input variables were analyzed, including service time, waiting time, and people waiting versus days of the week (0 to 6) to give initial insights of our model data. The service time in our data is the time when the patient started getting treated by a physician until the treatment ended. Data set (new features extracted) is used in this case to calculate patients in the queue, and it is used for every patient when they join the queue.

To calculate the sum of people in the queue, every time patients departed from the queue, we found the sum of the waiting time and the arrival time before counting the number of people still in the queue when a new patient joined the queue.

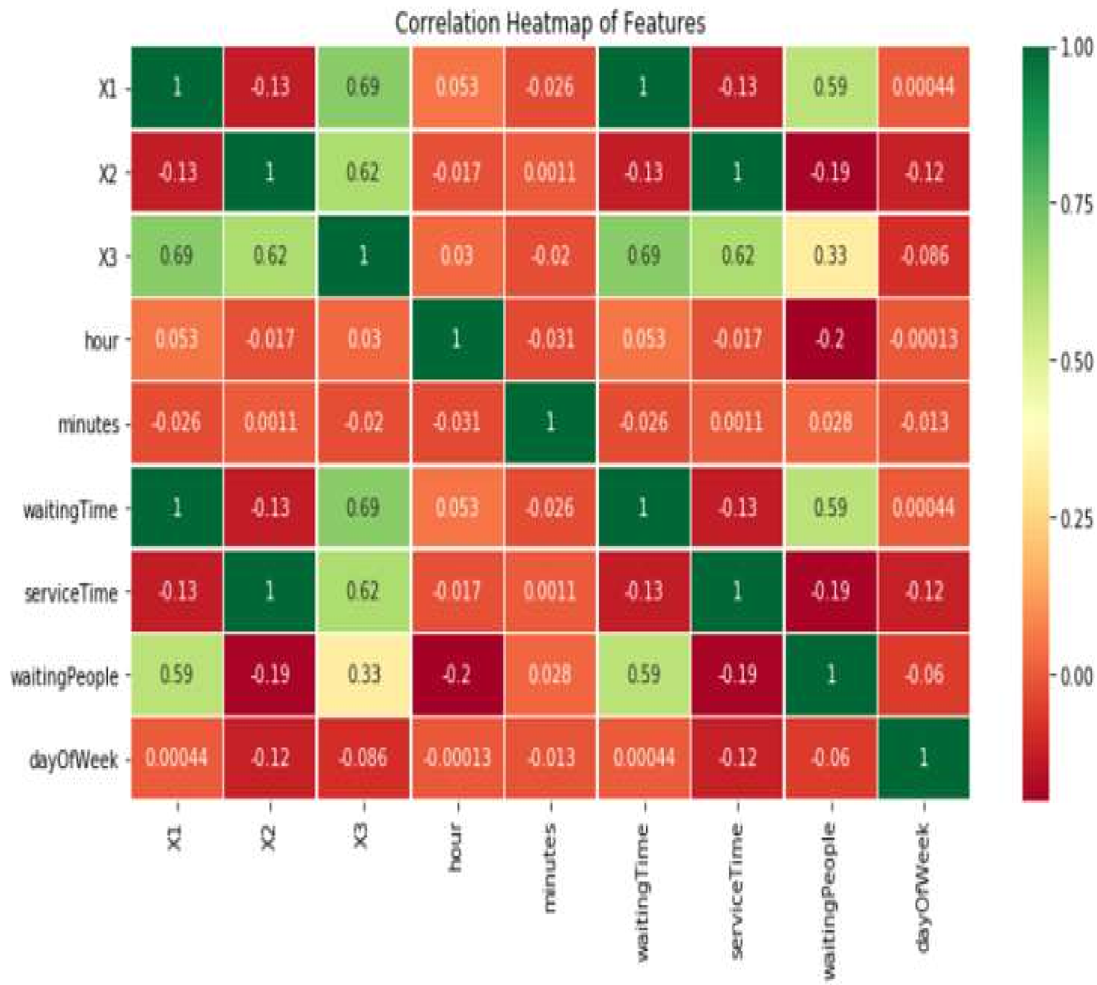

Figure 4.2. Correlation matrices, input and output variables.

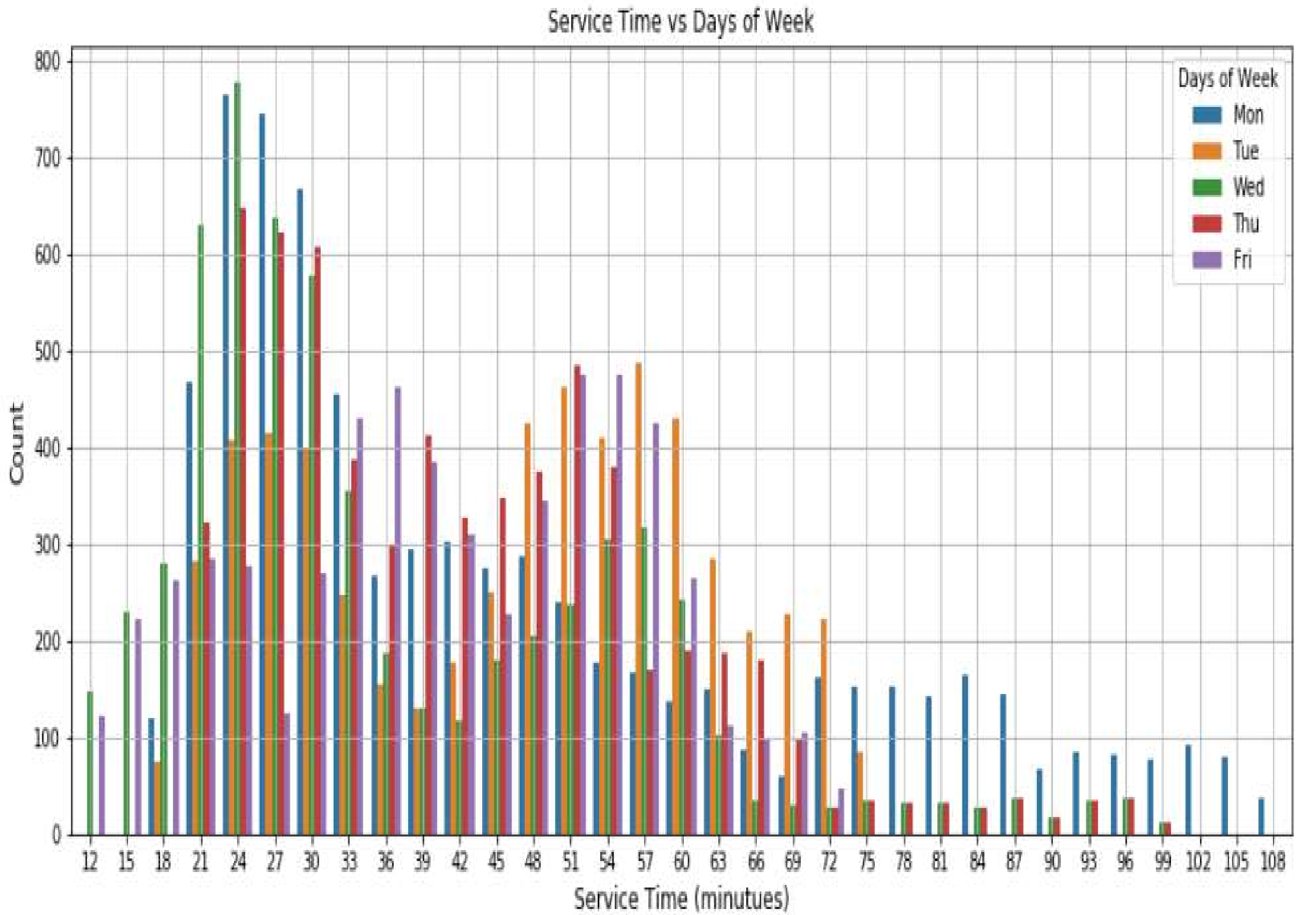

Figure 4.3. Service time of patients for days of week.

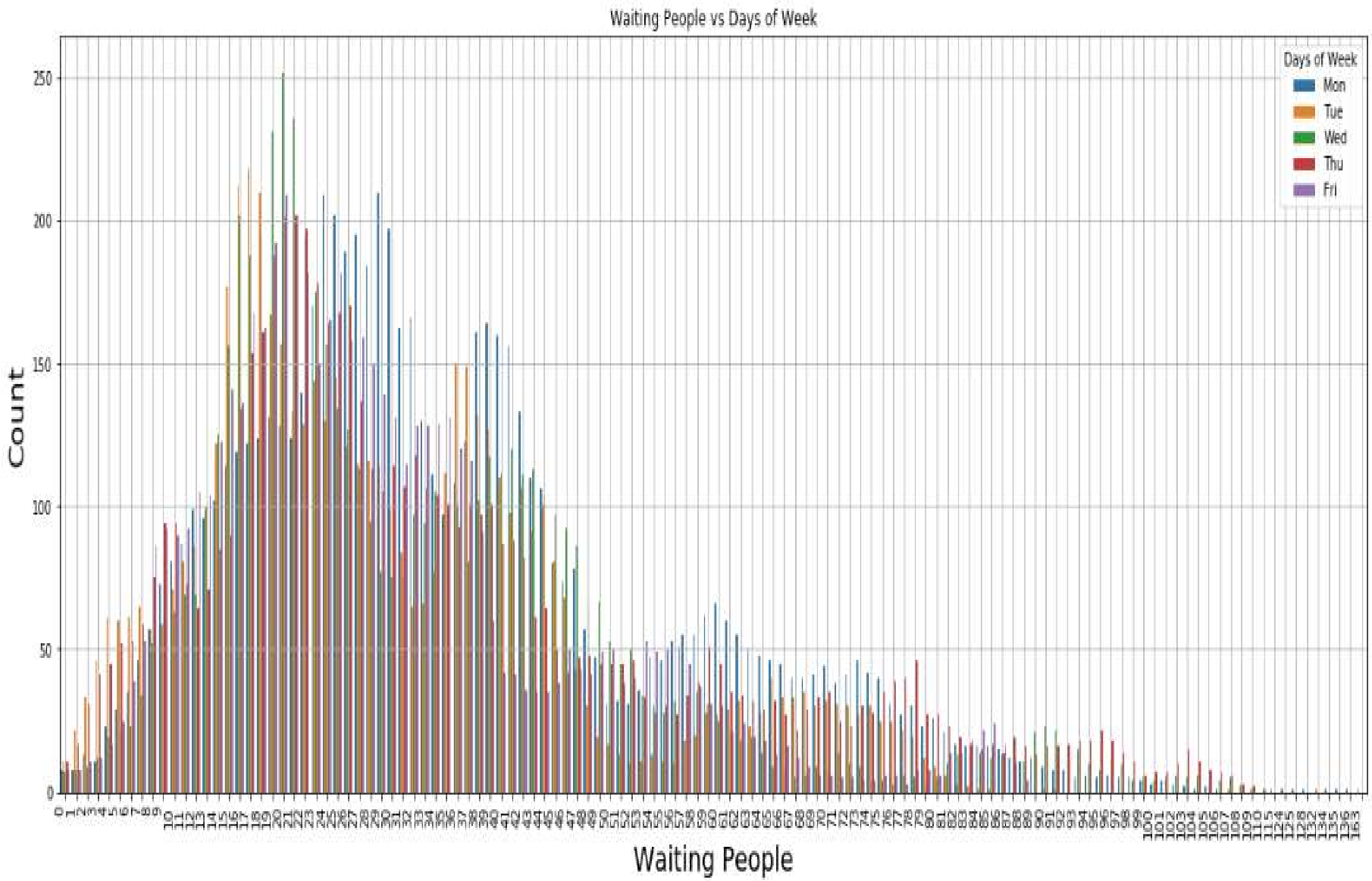

Figure 4.4. Number of patients waiting to join
the queue for days of week.

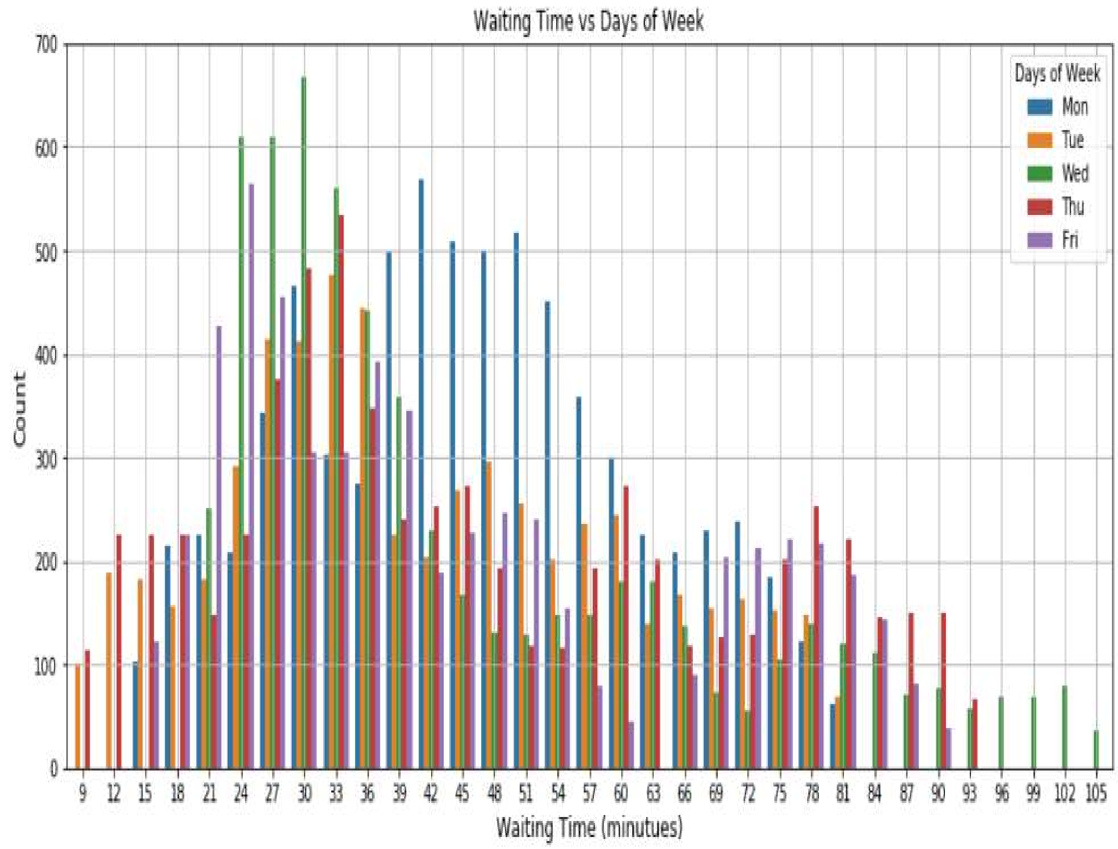

Figure 4.5. Waiting time of patients for days of week.

We faced different challenges while preparing and processing the prediction of patient waiting time in the queue. Queue priority is a difficult problem to solve due to stochastic patient arrival or randomly joining the queue. The patient priority is out of this paper's scope and will be analyzed in future work. Another challenge is that the number of servers is not apparent in the data set, though we assumed that we have only one server as mentioned above. These are very important in queue analysis, specifically when it

64

comes to queue theory calculation. Other factors may influence the patient's wait time, patients themselves, and their health history. It is a challenging task to determine these factors during queueing analysis. Also, the data has values that are larger than normal, so perhaps they are outliers. However, we used different techniques to remove outliers for machine learning, such as the standard deviation method.

4.2.2 Preprocessing and Feature Engineering

The feature selection (selection of predictors) is an essential element in the machine learning model structure that determines the model's performance [191]. There were main features extracted (e. g., minute, hour, and day) from the patient joining the queue in this study. Also, the patient’s waiting time in the queue and leaving time were extracted. The following three are the main features:

1. Day was in the range of Monday (0) to Sunday (6).
2. Time in hours from 0 to 23rd hour.
3. Time in minutes starting at 0 minutes and continuing the 59th minute.

The categorical features were encoded using mean target encoding and extracting the new features from current features in the dataset. We adopted this method (feature extraction) as presented by Kyritsis and Michel [192], which was applied in the bank. The mean target encoding was used to encode our data with the new features because it is a fast way to get most of the categorical variables encoded and gives higher cardinality features for regression problems [193].

4.2.3 Prediction and Algorithms Experimental

The experiment on machine learning in this study used TensorFlow version 2.0.0.-beta1 and Python version 3.7.3. Also, different libraries were used to prepare and pre-process the data, such as Matplotlib, DateTime and Pandas. Accordingly, to validate and test the sensitivity of the model's performance, we split our dataset into two factions: the test set was 15%, and the training set was 85%. The test set was kept hidden throughout the training process. Moreover, by validating our model, it means that we used a test harness was used to give a fair estimation of the model's performance for making predictions on new data because it shows how sensitive the method is to applied data or new data that can be introduced to the model. Different optimization algorithms were used for this model in order to find the best with the lowest MAE. MAE is one of the metrics used to measure the machine learning model performance accuracy; it gives an idea of the magnitude of the error. It calculates all recorded means for the absolute errors by subtracting the prediction value from the actual value, as shown in the Eq. (4.1):

$$MAE = \frac{\sum_{i=1}^{n} abs(yi - \lambda(Xi)}{n} \tag{4.1}$$

We applied different optimizer algorithms, including Adam, Adagrad, RMSprop, and SGD for the iterative update of network weights based on our data training and to describe the math behind the algorithms; equations (4.2) to (4.12) below are cited and summarized from Ruder (2016). Stochastic gradient descent (SGD) optimization algorithm does not change during training for all weight updates and the learning rate and maintains a single learning rate (termed alpha). A learning rate is maintained for each network weight (parameter) and separately adapted as learning unfolds. In contrast SGD performs a parameter update for each training example $x^{(i)}$ and label $y^{(i)}$:

$$\theta = \theta - \eta \,.\, \nabla_{\theta} J(\theta; x^{(i)}; y^{(i)}) \tag{4.2}$$

Adam (adaptive moment estimation) is a combination of Root Mean Square Propagation (RMSprop) and momentum. It can also be used instead of the standard stochastic gradient descent procedure to update network weights iterative based on training data (Kingma et al. 2014). Adam can also be used like Adadelta and RMSprop when storing an exponentially decaying average of past squared gradient v_t (Ruder 2016). Moreover, it keeps an exponentially decaying average of past gradients m_t, like momentum:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{4.3}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{4.4}$$

Where: m_t is estimates of the first moment (the mean) and v_t is the second moment (the uncentered variance) of the gradients, respectively, hence the technique's name. m_t and v_t are initialized as vectors of zero (as the authors of Adam observed that m_t and v_t are biased towards zero, especially during the initial time steps and when the decay rates are low (e. g., β_1, and β_2 are close to one)). m_t and v_t counteract these biases by computing bias corrected first and second-moment estimates:

$$\acute{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{4.5}$$

$$\acute{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{4.6}$$

Then, to update the parameters, we use these as shown in RMSprop, which yields the Adam update rule:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\acute{\upsilon}_t + \epsilon}} \acute{m}_t \tag{4.7}$$

RMSprop maintains per parameter learning rates which are adapted based on the average of recent magnitudes of the gradients for weight, such as how quickly it is changing. RMSprop is very effective but an unpublished, adaptive learning rate method proposed by Geoff Hinton in Lecture 6 slide 29 of his class (McMahan and Streeter 2014). In fact, RMSprop is identical to the first update vector derived from Adadelta, which is an extension of AaGrad optimization algorithm:

$$E[g^2]_t = 0.9E[g^2]_{t-1} + 0.1g_t^2 \tag{4.8}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} g_t \tag{4.9}$$

Where: $E[g^2]_t$ is the decaying average over past squared gradients. Adaptive Gradient (AdaGrad) maintains a per-parameter learning rate that improves performance on problems with sparse gradients, such as computer vision and natural language problems[194]. For each parameter θ_i at every time step *t,* AdaGraduses a different learning rate. Frist, AdaGrad's per-parameter is updated, which then is vectorized, for brevity; $g_{t,i}$ is set to be the gradient of objective function w.r.t. to the parameter θ_i at time step t:

$$g_{t,i} = \nabla_{\theta_t} J(\theta_{t,i}) \tag{4.10}$$

Stochastic gradient descent updates for each parameter θ_i at each time step *t* then becomes:

$$\theta_{t+1,i} = \theta_{t,i} - \eta.\,\theta g_{t,i} \tag{4.11}$$

AdaGrad modifies, in its update rule, the general learning rate ηat each time step t for every parameter θi based on the past gradients that have been computed for θi:

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\eta}{\sqrt{G_{t,ii} + \epsilon}} \cdot g_{t,i} \tag{4.12}$$

Where: $G_t \in \mathbb{R}^{dxd}$ is a diagonal matrix where each diagonal element i, i is the sum of the squares of the gradients w.r.t. θi up to time step t^{11}. And $\in$: Is a smoothing term that avoids division by zero (usually on the order of $1e{-}8$). Then, The Rectified Linear Unit (ReLU) was used in hidden layers. The ReLU activation function is a linear function that will output the input directly if it is positive (x); otherwise, it will output zero. (that is, if it receives any negative output it will return zero[195]). It is used in this model because it achieves better performance and is more comfortable to train when compared with other optimization functions (e.g., Sigmoid Function). ReLU can be written as Eq. (13):

$$f(x) = \max(0, x) \tag{4.13}$$

4.3. Results and Discussion

In this study, we aimed to apply a DL approach with queueing theory. DL is one of the machine learning methods based on artificial neural networks. DL's power is the libraries built, such as Keras, which help to create extensive networks quickly and easily. Also,the simulation model for the queueing system was built to compare with the DL model using the Ciw library. Ciw is a discrete event simulation (DES) library supported by Python for queue networks [196].

4.3.1. Deep Learning Model

Keras library by Python was used to apply DL mode and was trained with four input visible layers, 25 neurons for the first hidden layer, 18 neurons in the next hidden layer, and one output in theoutput layer. After 150 epochs of model training. Figure 4.6 shows the model predicted average waiting time against actual waiting time for the best outperform optimization algorithms (SGD). The blue color represents the real (actual) waiting time, and the orange color represents the predicted waiting time. It shows the predicted waiting time as being closest to the actual waiting time. The idea of what score a good/poor model can achieve only makes sense when it is interpreted in the situation of the skill scores of other models and trained on the same data.

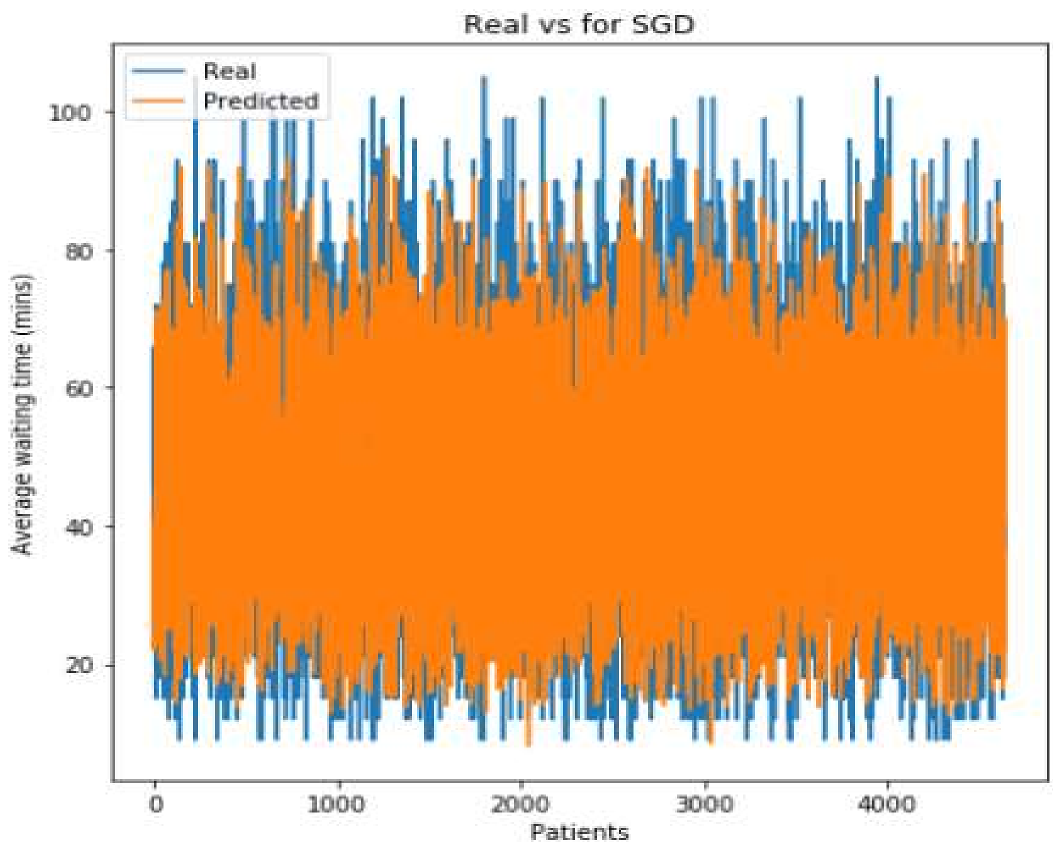

Figure 4.6. Waiting time predicted vs. actual for SGD algorithms.

In our experimental the four optimization algorithms are listed in order from high to low MAE in Table 4.1. The stochastic gradient descent (SGD) had the lowest MAE with 10.80 minutes, followed by RMSprop, and then Adam and AdaGrad optimization algorithm with around 12 minutes (Appendix A). After exhaustive tuning of all related hyperparameters used in the model, [25-18-1] values of the architecture were found to be suitable for the neural network for this model. On the plot of loss, the model has comparable performance on both training and validation datasets for all optimization algorithms as shown in Figure 4.7.

Table 4.1. Summary of the DL model (MAE results).

Optimization Algorithms	Network Architecture	Mean Absolute Error
AaGrad	[25-18-1]	12.78 minutes
Adam	[25-18-1]	11.16 minutes
RMSprop	[25-18-1]	11.14 minutes
SGD	[25-18-1]	10.80 minutes

The loss on both datasets maybe use this as a sign to stop training at an earlier epoch if these parallel plots start to depart consistently. Also, it shows the comparable skill on both train and validation datasets between the different optimization algorithms. The goal of using different optimizer algorithms is to change the attributes of our DL model, such as weights, learning rate, and reducing the losses and to reach the lowest MAE.

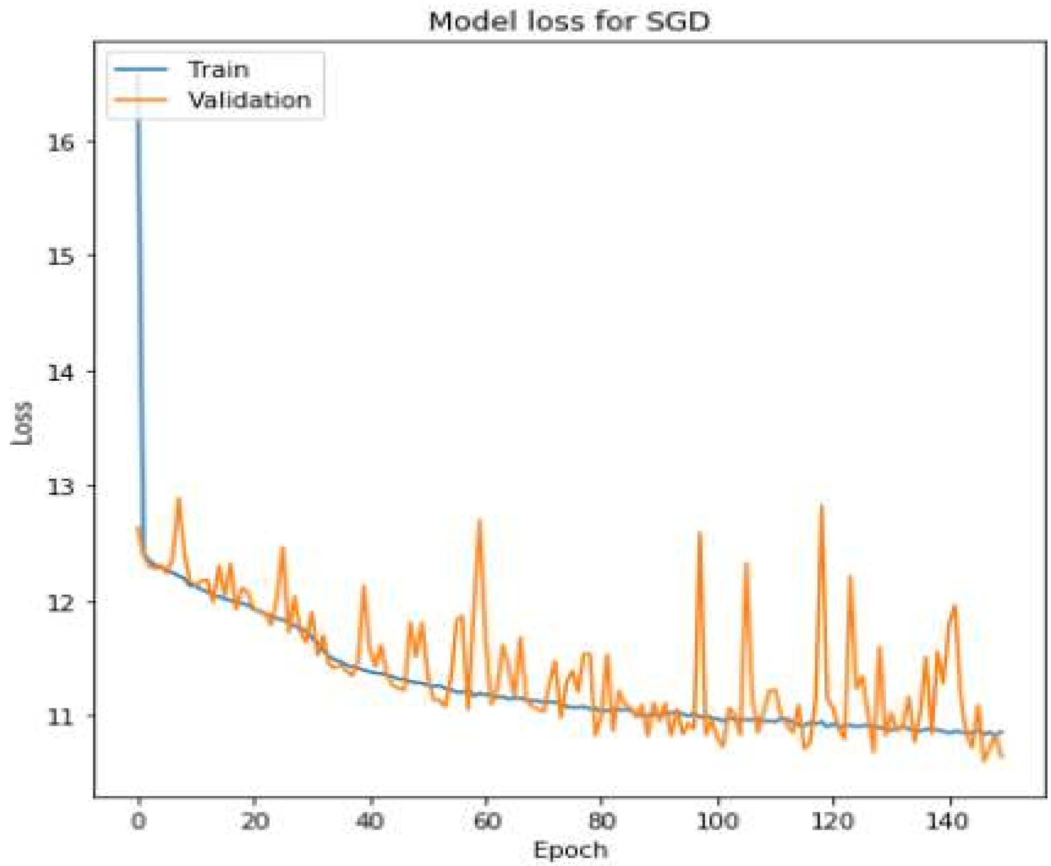

Figure 4.7. Plot of model loss on training and validation dataset.

4.3.2. Queueing Theory and Simulation Model

The classic approach of queue theory was used to simulate the model in this study. The arrival rate (λ) and the service rate (μ) have been calculated using the same data applied in the DL model. Data was used for one day as shown in (Appendix A Table A.1) and is assumed the probability distribution of service time as an exponential distribution. The number of arriving patients per unit of time follows the Poisson distribution. Because patients with level 3 through 5 acuities were used in this study, the queueing model of M/M/1 system for simulating the analysis was used to reflect the ER system. The model initially runs for 1,440 minutes (one day). To ensure that the simulation reflects reality, the model runs for ten simulations in a loop and takes warm-up time and cool-down times of 100-time units. Different seeds were considered every time, so each trial yielded different results. Then, to achieve a more confident answer, the mean effect was taken over the trial results (68.24, 87.07, 59.377, 61.08, 63.64, 63.01, 70.75, 88.66, 63.64, 58.29 in minutes). Consequently, with each trial, the model ran for one day + 200 minutes (1,640 minutes). Patient mean waiting time resulting from the simulation model was 58.29 minutes, and the service time was 53.27 minutes. Comparing QT, the results to DL models in the dataset, the mean waiting time was about 44.74 minutes which is close to DL models prediction.

Urgent and stochastic processes in the ER establish challenges to waiting time prediction. For example, the ER provides high acuity patients with effective emergency care but is typically not as efficient with patients seeking attention for non-urgent ailments. This leads to increased ER occupancy. While non-urgent patients wait in the ER, patients requiring highly urgent attention bypass waiting times, which may increase the waiting times for those who are non-urgent. Also, patients with non-urgent cases may vary from case to case due to patient-level attention needs (e.g., level, 3 to 5). However, it was established that low acuity care has an significant impact on overall ER waiting and service times for high acuity patients [197].

The goal of this study was to deliver a more accurate model for waiting time prediction and create an essential tool for reactive actions if ERs report long waiting time.

For instance, this model compares to other similar models for predicting waiting time in ER. Kuo et al.[83] developed models with a mean-square error accuracy between 0.15 to 0.22. The model included different significant variables, such as Patient's triage categories, arrival time, number of doctors (within three hours of the Patient's arrival), number of patients in a queue (for triage, consultation, and departure upon the Patient's arrival). The proposed model, Kuo et al.'s model is limited by implementing a local triage system (Hong Kong). Also, a regional triage system by Arha [85] estimated patient waiting time in an ER in Tennessee using a simple regressions model. Arhaused similar predictor variables (e.g., time of day, day of week, and month of year), and a mean square error as predictive accuracy [85]. To calculate this model variable and compare it with the proposed model requires collected clinical data. Pak et al. [86] also developed a waiting time prediction model for low acuity patients assigned to the waiting room with an overall accuracy of 20% mean squared prediction error; the proposed models with SGD and RMSprop algorithms reduced the prediction errors by 24% compared to model improvement in [86].

This study has some limitations, including data availability; not all ER information was included, such as a patient type of injury, X-ray process time, and laboratory test time. What is available in the dataset was extracted. Also, DL is known as data hunger; in this case, data was collected for only one year. As shown in the results, 10.80 minutes was reached as the lowest MAE, but this could decrease if the amount of data increases. In the experiment, 30,909 patients (level 3 through 5 acuities) were used in training after removing other levels (level 1 to 2 acuities) and missing data. Significant improvement was shown in waiting time prediction with available data when compared with a predicted average waiting time. Also, the model is simple enough to be implemented into an EHR system using relative information. The second limitation is the patient levels in the local triage system (assigned as levels 1 to 5) may differ geographically. For example, this data, levels 3 to 5 were set as low urgent, and levels 1 and 2 as high critical, but this may be different in other ER triage systems globally. The third limitation is this is a single location study, which could potentially impact the accuracy of the model, requiring more work to validate the model by using data from other ERs in different locations and with different populations.

4.4. Conclusion

This chapter proposed a novel model to improve the accuracy of waiting time prediction for low acuity patients using DL techniques and ER data. The study used historic queueing variables to predict patient waiting time in a queuing system alongside, or in place of, traditional approaches (queueing theory). The traditional methods may not be sufficient in real life applications due to the limitations of the method, such as unrealistic assumptions of the time distribution required to do queueing analysis.

In the current literature, research reported that the methodology applied to predict patient waiting time in ERs has limited accuracy. Furthermore, DL algorithms can reduce human error and achieve better accuracy, when compared with traditional methods. Thus, alternative techniques, such as DL algorithms, must be used to significantly improve ER efficiency. For this purpose, a novel model for waiting time prediction was created and as an essential tool for reactive actions if ERs report long waiting times. Furthermore, four optimization algorithms, including SGD, Adam, RMSprop, and AdaGrad, were compared to find the best accuracy considering MAE metrics. Also, algorithms were compared with traditional mathematical approaches and data was utilized from the triage monitoring system in Saudi Arabia. The results showed that the DL model achieved better prediction accuracy than the traditional approach. Moreover, the novel model produced in this study resulted in a 24% error reduction when compared to prior work on this topic[2].

[2] H. Hijry and R. Olawoyin, " Predicting Patient Waiting Time in Queuing System Using Multi Deep Learning Optimization Algorithms in the Emergency Room, " *International Journal of Industrial Engineering and Operations Management (IJIEOM), 2021, pp. 33-45, doi.org/10.46254/j.ieom.20210103*

CHAPTER FIVE

PREDICTING AVERAGE WAIT-TIME OF COVID-19 TEST RESULTS AND EFFICACY USING MACHINE LEARNING ALGORITHMS

5.1. Introduction

Due to the rising number of confirmed positive tests, the global impact of COVID-19 continues to grow. This can be attributed to the long wait times patients face to receive COVID-19 lab test results. During these lengthy waiting periods, people become anxious, especially those who are not experiencing early COVID-19 symptoms. Since the novel COVID-19 virus was first identified in Wuhan, China on November 17, 2019, the disease has resulted in numerous infections worldwide and record-high mortalities [198]. Most countries have begun offering tests for those who are symptomatic and suspected to have COVID-19. According to consistent global reports, COVID-19 test results have routinely been delayed by at least a week, and sometimes much longer. Others are faced with longer waiting times at overwhelmed testing centers and cannot receive swabs at all [199]. Furthermore, some COVID-19 results require more than a week due to bottlenecks in testing supply chains [200]. One or more weeks is considered an unsafe waiting time because people may not seriously change their behavior, such as limiting exposure to others while waiting to receive their results. This may be contributing to why COVID-19 is continuing to spread very rapidly.

Due to the rate of spread, where an average infected person can spread it to more than three other people, COVID-19 has been considered highly communicable. Hence, it has an exponential rate of increase since its outbreak [201]. As noted by numerous governments worldwide, the disease poses a massive threat to humanity, and it is only through early intervention and decisive action that nations can curtail it. However, this perception was not common among all governments. Some nations implemented early and effective control measures, whereas some countries overlooked the threat, thereby delaying control measure implementations.

One nation quick to execute containment measures was China. The government implemented unprecedented non-pharmaceutical interventions aimed at stopping the spread of the disease from its epicenter in Wuhan to other cities in the Hubei province through restrictions in travels in and out of the region. In addition, they closed all learning institutions and suspended air, road, and rail transport, and isolated the reported cases [202]. Also, between February 2 and March 30, 2020, the government of Saudi Arabia announced precautionary measures by suspending flights, schools, public, private, and university education institutions and entry to individuals wishing to perform Umrah in Mecca or visit the Mosque in Medina [203].

Since the outbreak spread quickly, managing delays of COVID-19 test processes became an essential part of hospital management during the pandemic for several reasons. For example: (i) the long wait to get test results may have affected the healthcare system later by increasing the treatment demand and the capacity. For instance, cases were not adequately being controlled in the early stages. For asymptomatic people (those without symptoms), they take the test and wait for the results. In the interim, they may continue to have contact family and relatives, increasing the spread of the disease [204], (ii) the delays of test results disproportionately affects people with adverse health conditions, such as older people or those suffering from chronic diseases [205], (iii) long wait times for results disrupt life, such as school and work, and make it difficult for public health administrators to adapt their responses to the correct people (those who are infectious and people to whom they may have spread the disease). For example, in the United States, some schools and universities announced decisions for the Spring and Summer 2021 semesters, where students would continue with online education platforms[206], [207], (iv) due to a record high demand for the COVID-19 tests, labs continue to be overwhelmed. Testing centers in California and Texas were forced to close because of a surging demand [208].

The ability to accurately predict the waiting time for COVID-19 test results may increase patient satisfaction and effectively improve the healthcare system (Conner 2020). This improvement will be accomplished by predicting the waiting times for COVID-19 test results based on predictive factors such as test location and labs where patients took the COVID-19 test (as queues or lines for patients). Even though the patients are not in a physical line, they still count as people waiting for service to be finished. Therefore, when patients (e.g., 200 patients) send their tests to facility 1 (queue1), and the next group of patients (e.g., 200 patients) goes to the second facility (queue2), when the third group of patients has to do a test, decision makers can determine how much waiting time is left in facility 1 versus facility 2 using a prediction. If facility 2 shows a lower waiting time, the third group can be assigned to facility 1. This process is repeated for a number of facilities (queues) and a number of patients. This example shows how patient waiting time analysis is essential based on the predictive factors including the sending facility (location where the patient took the exam, such as hospitals).

Predicting COVID-19 test result waiting time can enable healthcare management and governments to respond to pandemics more accurately. In this research, multiple machine learning (ML) algorithms were leveraged to forecast COVID-19 test result waiting times based on different factors to support healthcare management using real-life data from *HESN* system in Saudi Arabia. Also, these predictions allow for informed decisions during the pandemic, which may motivate other researchers to conduct additional work by applying models to the other areas in the Middle East, Africa, and other areas with similar populations. Furthermore, this study's novelty lies in a huge amount of analyzed data which has been recorded throughout the pandemic. Moreover, multiple machine learning algorithms are implemented which will add to the current literature and may be used to anticipate and better optimize risk management, such as managing situations where the ICU capacity is exceeded.

5.2. Methodology

In this section, ML algorithms were applied to predict the waiting times for COVID-19 test results based on predictive factors such as receiving lab and sending facility. Different algorithms were trained, including network (NN), support vector regression (SVR), linear regression (LR), K-nearest neighbor regression (KNN), gradient boosting regression (GBRT), extra trees regression (ET), decision tree (DT), and random forest (RF). Also, different performance measures (metrics) were used to evaluate the models, such as mean square error (MSE), mean absolute error (MAE), root mean square (RMSE) and R-Squared to estimate and evaluate the model performance.

Finally, the proposed models were compared to determine which one works best across all predictive factors using the lowest measures indicated by evaluation metrics.

The proposed methodology stages are presented, and a flowchart is shown in Figure 5.1. Each step is illustrated in the following subsections.

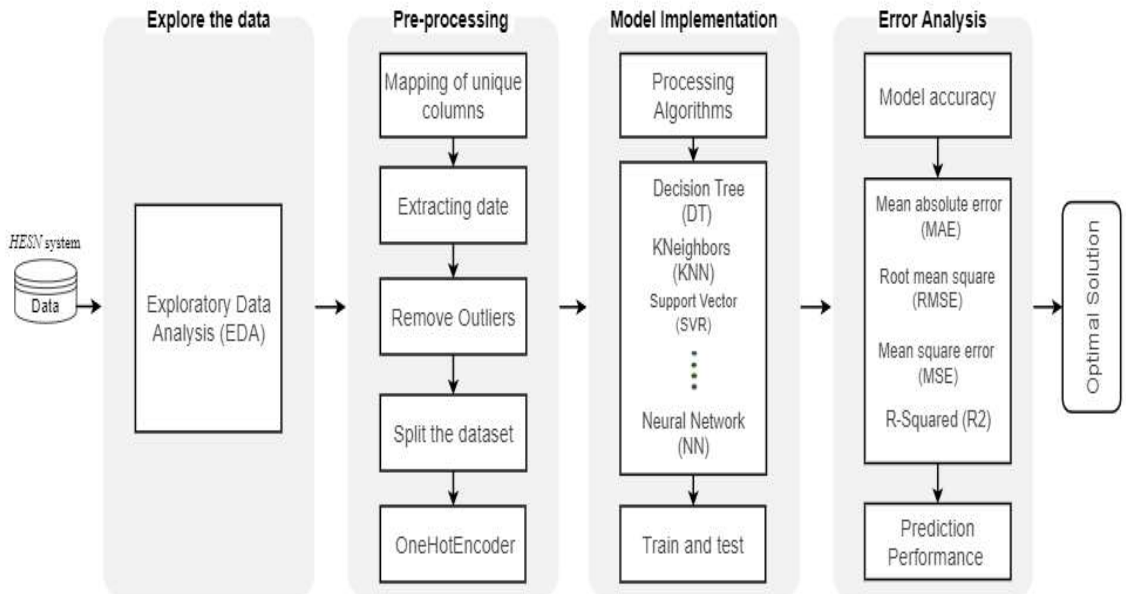

Figure 5.1. A framework of proposed methodology (lab test results).

5.2.1 Data Preparation

Data were used from the Saudi Arabian Ministry of Health's *HESN* system. Data were obtained between March and July of 2020 and comprised 54,730 patients (around 70.8% were negative cases and around 23.3% were positive cases) as shown in Table 1. *HESN* is an online platform that monitors disease management and offers health professionals and decision-makers accurate information (MOH 2020). Data demographics included patient age, gender, and nationality, as well as test status, result status (complete and rejected), receiving lab, result interpretation (positive and negative), date time required (the date that patient took the test), and result date time (the date of receiving the results). Also, the data included results from COVID-19 testing in multiple departments within one hospital, including an emergency room. From the required date and result date, waiting time was calculated, which is the difference between the date and time the test was requested, and the date and time results were received. Some of the required date-time categories came without time of test taken in the dataset but these still had dates provided. For this data, we assigned a time placeholder of 00:00:00.

5.2.2. Exploratory Data Analysis and Features Importance

As an initial step of this project, different tables and plots were derived from the data and explored to understand the trends therein to achieve the best outcomes (Appendix B). First, the dataset was summarized based on the input's factors such as gender, result status, and result interpretation, as shown in Table 5.1. A total of 54,730 patients were recorded in the dataset, which was 31.3% female and 68.7% male. A total of 54,730 tests were conducted; 53,016 tests were completed (around 96.8% of total data); three were preliminary and around 1,709 were rejected (around 3.2% of total data). In result interpretation, the negative results of the dataset totaled 38,750 (around 70.8% of total data) and 12,763 positives (around 23.3% of total data). As expressed in the table, a massive number of cases were negative.

The large negative rate reflects the expanded testing conducted by the Ministry of Health in Saudi Arabia. According to the Division of Public Health, "Expanded Testing is considered one of the initiatives carried out by the government to respond to COVID-19 outbreak, which has been launched through a few stages. It aims to benefit both citizens and residents by expanded testing to evaluate the COVID-19 spread" [209].

Second, the waiting times for COVID-19 test results were analyzed within one week of wait time using the dataset because the literature noted complaints that the waiting time of test results are delayed by more than one week [199].

Table 5.1. Summary statistics of dataset between March and July. 2020.

	Statistical Summary		
	Frequency	Percent	Cumulative Percent
Gender			
Female	17,135	31.3	31.3
Male	37,595	68.7	100.0
Result Status			
Complete	53,016	96.8	96.8
Pending	2	.0	.0
Preliminary	3	.0	.0
Rejected	1709	3.2	100.0
Result Interpretation			
Negative	38,750	70.8	70.8
Positive	12,763	23.3	94.1
Rejected	1939	3.5	97.6
Repeat Sample	1,278	2.4	100.0
Total	54,730	100.0	

Table 5.2 shows how many patients waited between less than 1 day to more than 5 days. The waiting times were divided into groups (waiting time <1 day, between 1 and 2.5 days, between 2.5 and 5 days, and more than 5 days). As shown below, 5.1% of patients waited for less than 1 day, 74.4% waited for their results between 1 and 2.5 days, and 19.8.% incurred a waiting time between 2.5 and 5 days. Only 0.7% had waiting times of more than 5 days.

Third, waiting times based on other factors were analyzed including patient gender, result status, and result interpretation, as shown in Table 5.3. Based on the initial results, there was no statistical significance based on gender difference for the wait time; the average waiting time for both genders were roughly the same at approximately 2.4 days each. Around 51,005 patients who completed test results waited for 2.4 days, and for two patients, the result status was pending for 2.9 days. Around 38,254 patients waited 2.4 days for negative results and 12,101 patients with positive results waited for 2.3 days.

Table 5.2 Waiting times analysis between less than one (1) day to more than five (5) days.

Waiting Time Grouped			
	Frequency	Percent	Cumulative Percent
Less than 1 day	2,785	5.1	5.1
Between 1 and 2.5 days	40,688	74.4	79.5
Between 2.5 and 5 days	10,885	19.8	99.3
More than 5 days	372	0.7	100.0
Total	54,730	100.0	

Table 5.3. Summary for Mean waiting time based on selected factors.

	Statistical Summary		
	Mean	**N**	**Std. Deviation**
Gender			
Female	2.398	15,944	0.887
Male	2.405	36,299	0.887
Result Status			
Complete	2.496	51005	0.891
Pending	2.954	2	2.011
Preliminary	2.273	3	0.951
Rejected	2.408	1,233	0.891
Result interpretation			
Negative	2.403	38,254	0.890
Positive	2.399	12,101	0.893
Rejected	2.375	597	0.905
Repeat Sample	2.370	1,291	0.918

Then, the average waiting time per lab was analyzed, as shown in Table 5.4. There were 14 labs in the dataset. Only 5 labs were used in the training process and these labs had more than 50 recorded cases. The names of the labs were coded by numerals, e.g., lab 1 to lab 5. This was done to simplify the analysis. Most labs' mean waiting time was approximately 2.0 to 2.5 days.

Table 5.4. Summary of Mean waiting time based on receiving labs.

	Statistical Summary (receiving labs)		
	Mean	**N**	**Std. Deviation**
Lab 1	2.499	13,958	0.879
Lab 2	2.063	108	2.602
Lab 3	2.305	368	2.344
Lab 4	2.426	1,168	0.861
Lab 5	2.396	39,128	0.889

The highest mean waiting time by receiving lab was recorded for Lab 1, who had a 2.5-days average turnaround time, as compared to the lowest waiting time of 2.0 days at Lab 2.

An extra regressor was used to calculate feature importance, as shown in Figure 5.2. The input features were placed on the y axis. On the x axis, an impotence score was placed, which is also illustrated in the score figure below. The receiving lab and sending facility had the most contribution toward the output prediction. Finally, the basic process of analyzing the dataset helped us choose the best features to apply in training models. Moreover, to maximize the best outcomes of the prediction models, at the end of the study, the actual and predicted results based on those input factors were compared.

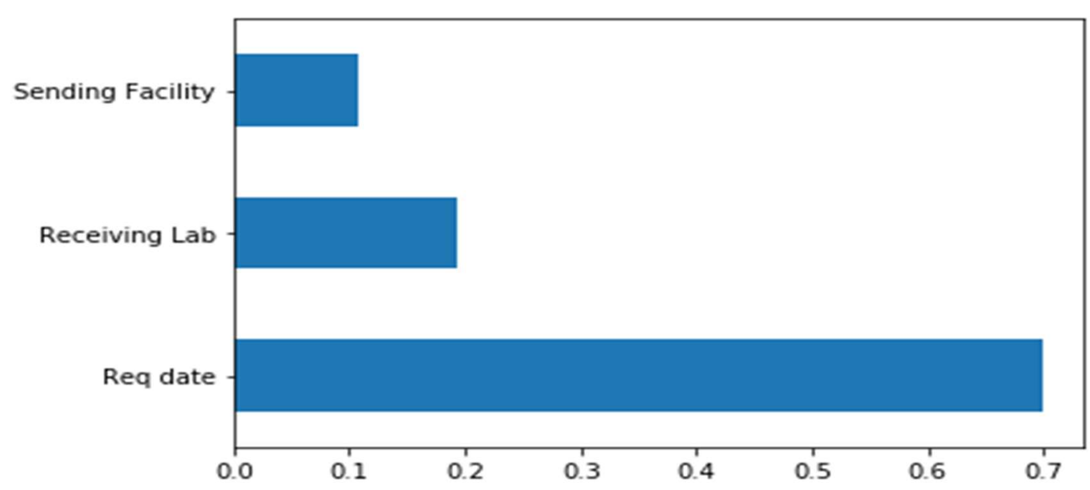

Figure 5.2. Features importance tests for retained features.

5.2.3. Data Conversion

Data preprocessing is a necessary step in ML problems. Different basic programs were developed in Python to explore the data and identify missing value and outliers, encode string value, split dataset and feature scaling. All the rows with missing values were deleted from the dataset, and the outlier values were analyzed by removing them from the dataset before training. Also, irrelevant features such as patient IDs and names were removed from the dataset. One-hot encoding was used to encode all the categorical data into binary. Feature selection is an essential part of the ML model structure that determines the model performance and was therefore incorporated into our process as well. Also, the input factors were checked to ensure they positively correlated with outputs. Variables with similar information were deleted to improve the performance of the models, which allowed the algorithms to learn faster and decreased overall bias. Similarly, we checked the input factors that had an effect on the waiting and later in the training process, the factors that were not directly related to waiting time were removed.

5.2.4. Prediction and Evaluation Optimal Outcomes

In this stage, two techniques were used. The data was first split into Train and Test Sets. Next, K-fold Cross-Validation was implemented for the machine learning algorithms to evaluate all models and to split up the training dataset (see Appendix D). Initially, the data was split into two datasets (20% and 80%): the first set was used to test the model and consisted of data that the model had not encountered prior. The second dataset was used to train the K-fold cross validation model. Once that was finished, the model checked its validity with the hidden dataset. Then to avoid overfitting, Cross-Validation was used again to estimate the performance of machine learning regression algorithms with less variance than a single train-test set split [210]. The dataset was split into k-parts (K being equal to 5). The CV data also split again into three sets (train, validation, and test) sets; the training set is split into *k* smaller sets (see Figure D. 1). Also, it was essential to use metrics in machine learning applications to evaluate the algorithms. The four standard metrics used in this research to evaluate the prediction on regression models were MSR, MAE, RMSE, and R-Squared [192].

All the modeling steps, including data preparation, preprocessing, training and testing, and parameter tuning, were achieved using Python 3.7. In the regression models, 8 regression algorithms were used to spot check and train the dataset. First, we applied linear algorithms, such as multiple linear regression (LR). Then, nonlinear algorithms, such as support vector (SVR), and K-nearest neighbors' regression (KNN), were applied. Also, fully connected neural network models were trained with two hidden layers (the first layers = 6 neurons and the second hidden layers = 4 neurons). Finally, the results for different algorithms were compared to determine the best choice from the prediction model. This is indicated by different metrics versus applied algorithms in the results section, as presented in Table 5.5.

5.3. Results and Discussion

Several models were evaluated by visualizing their actual and predicted waiting times for COVID-19 test results based on sending facility and receiving lab, as shown in Figures 3 and 4 below. COVID-19 test result waiting times were predicted for 54,730 patients recorded across four facilities and 5 testing labs. DT, ET and RF reported as the best performing algorithms among all models indicated by R-Squared and RMSE metrics, as shown in Figure 5.5.

Sending facility is the place where patients must go to receive a COVID-19 test. These facilities include hospitals, clinics, or testing centers. There were 171 facilities in the dataset and the waiting time per facility was predicted using multiple regression (linear and nonlinear) and neural networks. Sending facilities were mapped based on geographical location, for example middle centers, northern centers, southern centers, and northwest centers. All centers in the southern area were grouped under one area called "southern centers." Figure 5.3 (a and b) shows the predicted waiting times for COVID-19 test results and actual versus sending facility. The red dots in Figure 5.3(a) represent the actual waiting time for patients' test results, and the blue dots in Figure 3(b) represent the predicted waiting times. As shown, the most waiting time occurred between less than 1 day to 6 days, with a mean waiting time of around 2.5 days.

The models predicted the waiting times for COVID-19 test results based on receiving labs, Figure 4 (a and b) shows predicted and actual versus receiving labs. Receiving labs are where the COVID-19 tests are sent for analysis. The number of test cases were in each lab, and how long the waiting times were during the lab process, are illustrated in Figure 5.4(a). Also, receiving labs were mapped from real lab names to be Lab 1, Lab 2, Lab 3 and so on. As shown in Figure 5.4, Lab 1 and Lab 4 had the highest waiting times; each passed seven days with a few cases, whereas the majority of other labs (2, 3 and 5) were between 1 to 5 days wait time.

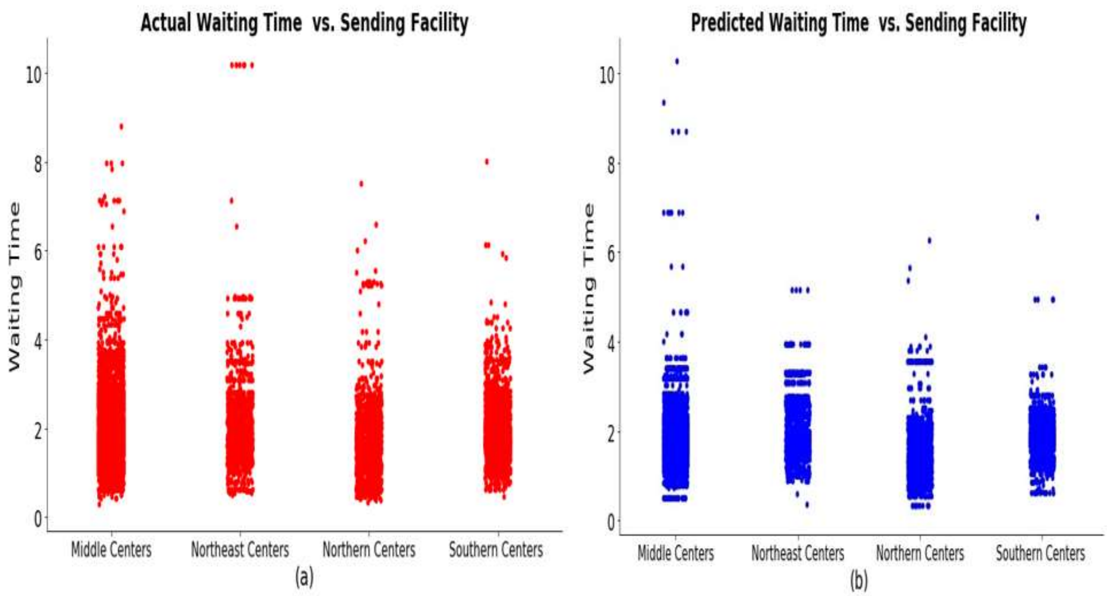

Figure 5.3. The waiting time of COVID-19 test results (actual and predicted of facilities).

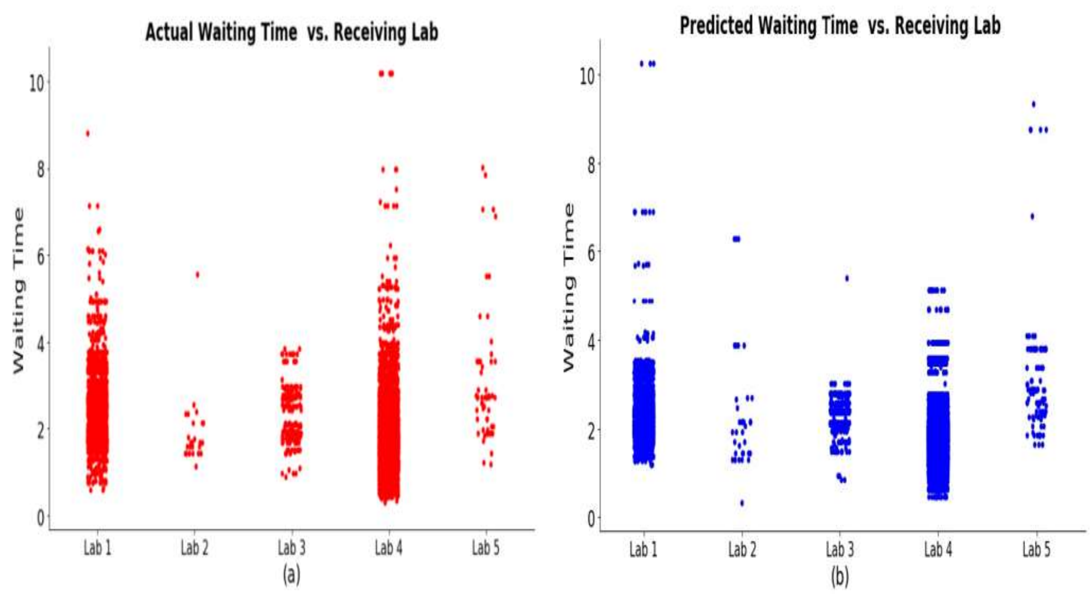

Figure 5.4 The waiting time of COVID-19 test results (actual and predicted based on labs).

The overall results of all models' predictions performance were investigated using evaluation metrics, as shown in Table 5. As shown below, the results of model performance varied across all algorithms. For example, out of all the algorithms, the lowest performance with MAE was about 0.40 to 0.53, around 0.38 to 0.54 with MSE, and around 0.62 to 0.74 with RMSE. It is worth noting an interesting result: of the models that applied R-Squared, only three algorithms performed highly. These models were decision tree regression (DT), extra tree regression (ET) and random forest regression (RF). The results are summarized in Table 5 below.

Table 5.5. Summary of models' algorithms using evaluation metrics. Note: mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE).

Algorithms	**Models**			
	MAE	MSE	RMSE	R-Squared
Decision Tree Regression (DT)	0.424	0.388	0.623	0.365
Extra Tree Regression (ET)	0.423	0.389	0.623	0.366
Gradient Boosting Regression (GBRT)	0.464	0.442	0.665	0.276
K-Neighbors Regression (KNN)	0.449	0.459	0.677	0.249
Linear Regression (LR)	0.534	0.574	0.757	0.062
Random Forest Regression (RF)	0.423	0.388	0.623	0.366
Support Vector Regression (SVR)	0.401	0.428	0.654	0.300
Neural Network (NN)	0.498	0.547	0.739	0.105

The algorithms were ranked based on performance using a combination of matrices. The prediction performance was compared using R-Squared versus RMSE across all models, as shown in Figure 5. The highest performing model found to predict the waiting time for COVID-19 test results was DT, followed by ET and RF, as shown in the top left corners of the figure. These models resulted in the lowest RMSE and highest R-Squared performance among all algorithms. As revealed in the figure, DT performance results were not far from ET and RF; in fact, they were almost the same. This makes sense because ET and RF are also tree algorithms; however, DT is the simplest regarding overall usability (Appendix C).

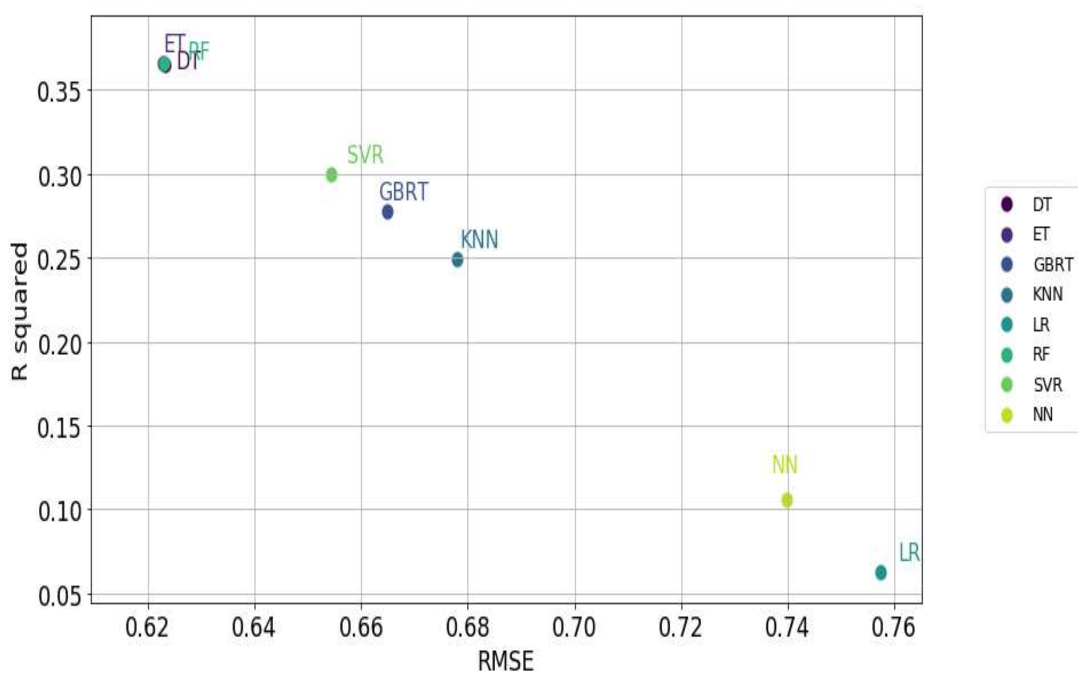

Figure 5.5. Comparison of prediction models (RMSEVs. R-Squared).

COVID-19 test results sometimes require more than a week due to bottlenecks in testing supply chains. This is considered an unsafe waiting time, which may be why the COVID-19 is continuing to spread so rapidly. Furthermore, the delay of test results disproportionately affects people with adverse health conditions, such as older people or those suffering from chronic diseases. Managing delays of the COVID-19 tests process became an essential part of hospital management during the preparation and planning of increased medical needs overcoming the uncertainty time of pandemic [205].

This study aimed to provide the healthcare division with more accurate models to predict the waiting times for COVID-19 test results based on selected factors using machine learning algorithms. The models are an essential tool for responsive and proactive action during the pandemic. If healthcare providers and authorities have prior knowledge of average waiting times for labs using prediction, it can greatly improve the healthcare system. For example, they can reduce waiting times of longer than 2.5 days by improving the services through sending test samples to labs with fewer tests, as predicted in Figure 4 in the results section. Similarly, as shown in Figure 3, it is easy to identify which center is struggling with immense numbers of tests and long waiting times. Also, as noted in the literature, there are complaints that the waiting time for test results have been delayed in some cases by more than one week [199], [204]. The results of this study show waiting times based on patient testing centers and labs, within ten days. However, the findings show that the average waiting time in the prediction within one week is 2.5-days as compared with complaints in the literature.

Some studies in the literature have attempted to propose models for COVID-19 prediction using different methodologies. For example, classifier models and mathematical approaches to predict the COVID-19 symptoms based on patient hospitalization, death, and ICU beds needed as suggested in [98], [99]. Also, Zoabi and Shomron proposed machine learning models to predict COVID-19 diagnosis based on symptoms using Several features such sex, and age [102]. These studies are limited by instigating local data of COVID-19 cases prediction. Also, there is no study in literature attempting to predict COVID-19 symptoms considering the waiting time of test results using multiple machine learning algorithms, such as a regression and Neural Network as presented in this research. Moreover, recent research in the literature reported small sample sizes and model accuracy as limitations in proposed models' prediction for diagnosis and prognosis of COVID-19 [98].

There were some limitations in this research. It is necessary to clarify that the dataset used in this research did not include certain information that may affect the waiting times, such as how long the test samples took to transfer from testing centers to receiving labs. The reader should be aware that COVID-19 policies and restrictions vary by jurisdiction, which could affect the model's stability. For example, the supply of detection kits, mask-wearing, or isolation policies may differ in different countries or provinces. Also, this study investigated the COVID-19 test result waiting time issue in only one particular jurisdiction, (i.e., Saudi Arabia), which may have an impact on the global generalizability of the findings.

5.4. Conclusion

This study's novelty lies on a huge amount of data analyzed which is recorded during the pandemic and it contributes to machine learning literature by implement multi-algorithms (such as NN, SVR, LR, KNN, GBRT, ET, DT, and RF) to predict waiting times for COVID-19 test results. A significant improvement was achieved in model performance using different metrics including MSR, MAE, RMSE, and R-Squared. The most accurate model was DT, followed by ET and RF. These models resulted in nearly identical performance ratings, though DT outperformed other ML algorithms in prediction accuracy, simplicity and explainability than ET and RF.

Research in the literature reported that the mean waiting time of COVID-19 test results was delayed by at least a week, and sometimes much longer, which motivated this study for further analysis. On the other hand, the models presented in the literature have small sample sizes and limited accuracy. This research provided an essential tool to predict waiting times for COVID-19 test results using multi machine learning algorithms. The model can reduce error prediction and achieve better accuracy, when compared with studies in literature. Moreover, the proposed models can help medical decision-makers prepare for future demands. It gives the healthcare providers an initial measurement of the COVID-19 tests process and the action needed to improve the service (e.g., increases in the centers or speed up the process). Furthermore, the models can provide data to inform guidelines and provide decision makers with the proper prediction tools to prepare against possible threats and consequences for future waves of COVID-19[3].

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CHAPTER SIX

SUMMARY, CONTRIBUTIONS AND FUTURE WORK

6.1 Dissertation Summary

Many hospitals consider the length of time waiting in queue to be a measure of emergency room (ER) overcrowding. Long waiting times plague many emergency departments, hindering their ability to effectively provide medical attention to those in need and increasing overall costs. Advanced techniques such as machine learning and Deep Learning (DL) have played a central role in queuing system applications. In this dissertation, the crowding problem in the ER is analyzed by studying different factors which may affect overcrowding using different ML algorithms. The first measure factor studied in this dissertation is patient length of stay (LOS) during vital time.

Hospital emergency rooms (ERs) in vital locations face high patient demands during peak events such as the annual Islamic pilgrimage (the Hajj event) in Mecca, Saudi Arabia, the New Year celebration ceremony in New York City, New York, the World Cup, etc. Variable patient arrival rates and hospital conditions, particularly the availability of beds for inpatients, impacts long waiting times and LOS, causing pain and dissatisfaction to patients. Patient LOS is chosen to be a measure of ER overcrowding as a compliance measure set by most hospitals. Clinicians need to get an opportunity to be proactive in ER overcrowding crises, specifically in the case of peak days. For this purpose, a model to forecast Hajj patient LOS (Chapter 3) was built using machine learning algorithms such as ANN, linear regression, and logistic regression through predictive input factors such as patient age, mode of arrival, and patient’s type of condition in the ER. The modeling result's prediction accuracy for ANN was 78.29%, and overall, for linear regression was 72% and 50% for the logistic regression model. All models did not give an ideal prediction accuracy; they were expected to be better than 80%. This reason is created by factors selection or insufficient input variables, but they still has better accuracy compared with previous study Gul and Fuat's [211]. The best model resulted from Gul and Fuat's study at 63% for LOS prediction. Therefore, using machine learning algorithms to forecast ER LOS allows clinicians to prepare for high levels of congestion and provide insights to determine the LOS of patients during vital times. For future directions, other forecasting techniques, such as support vector machine and random forest, can be used to compare to the current results.

The second measure analyzed in this dissertation is waiting time in queue system. Deep Learning (DL) algorithms can reduce human error and achieve better accuracy when compared with traditional methods. Thus, alternative techniques, such as DL algorithms, must be used to significantly improve ER efficiency. For this purpose, in Chapter 4, a novel model for waiting time prediction was created and as an essential tool for reactive actions if ERs report long waiting times. Furthermore, four optimization algorithms, including SGD, Adam, RMSprop, and AdaGrad, were compared to find the best accuracy considering MAE metrics. Also, algorithms were compared with traditional mathematical approaches and data was utilized from the triage monitoring system in Saudi Arabia. The results showed that the DL model achieved better prediction accuracy than the traditional approach. Moreover, the novel model produced in this study resulted in a 24% error reduction when compared to prior work on this topic (Pak et al. 2020). As part of future directions, the service time of patients with the same acuity levels could be predicted and different machine learning algorithms could be compared this study. The last measure studied in this dissertation is lab test results using COVID-19 data.

Due to the rising number of confirmed positive tests, the global impact of COVID-19 continues to grow. This can be attributed to the long wait times patients face to receive COVID-19 test results. During these lengthy waiting periods, people become anxious, especially those who are not experiencing early COVID-19 symptoms.

In Chapter 5, this study aimed to develop models that predict waiting times based on COVID-19 test results using different factors such as testing facility, lab location, and date of test. Several machine learning algorithms were used to predict average waiting times for COVID-19 test results and to find the accurate model. These algorithms include neural network, support vector regression, K-nearest neighbor regression, etc. COVID-19 test result waiting times were predicted for 54,730 patients recorded during the pandemic across 171 hospitals and fourteen labs. Among the eight proposed models, the results showed that decision tree regression performed the best for predicting waiting times using COVID-19 test results. A significant improvement was achieved in model performance using different metrics including MSR, MAE, RMSE, and R-Squared. The best models selected was DT, followed by ET and RF. These models resulted in nearly identical performance ratings, though DT outperformed other ML algorithms ET and RF in prediction accuracy, simplicity, and explainability. The proposed models could be used to prioritize testing for COVID-19 and provide decision makers with the proper prediction tools to prepare against possible threats and consequences of future COVID-19 waves.

Models in this dissertation provide a guideline for waiting time analysis in the queue—not only in healthcare, but also in other sectors include industry and services. Finally, to accurately capture the crowding indicators at any given time, it is recommended that further research should be conducted to improve predictive accuracy and create more predictor variables such as staffing physicians, practitioners, and nurses.

6.2 Contributions

The overall contribution of this research is providing new methods for predicting patient waiting time and crowding reduction in healthcare systems. It produces a novel model to reduce the error prediction when compared to prior work on this topic. In this dissertation, the main contributions to body of knowledge are summarized as follows:

6.2.1 Length of Stay (LOS) Prediction:

1. Developed a new algorithm to predict patient LOS considering new predictors factors such as age, mode of arrival, number of patients, gender, provisional diagnostic category, ICU admission, and number of comorbidities apart from similar studies in the literature.
2. The provided models, include artificial neural networks, linear regression and logistic regression, which performed as the first attempt to forecast ER LOS using Hajj patient who attended ER during the peak Hajj period.
3. Provided a new method for data expanding and factors extracting considering small data availability.
4. Provided a prediction tool for health management to prepare for high levels of congestion and provide insights to determine the LOS of patients during vital times.

6.2.2. Waiting Time in Queue System Prediction:

1. Developed a Deep Learning (DL) model and provided a new method to use alternative techniques alongside or in place of queuing theory to predict and prioritize waiting time in a queue system using real data from Electronic Health Records (EHR).
2. Provide insights to ER medical staff to determine patient waiting time in the queue.
3. Developed new algorithms (including Adam, Adagrad, RMSprop, and SGD) to reduce error prediction using a mean-square error (MAE) patients with low acuity using queueing predictor variables. For example, Pak et al. (2020) developed a waiting time prediction model for low acuity patients assigned to the waiting room with an overall accuracy of 20% mean squared prediction error; the proposed models with SGD and RMSprop algorithms reduced the prediction errors by 24% compared to model improvement in Pak et al. (2020).
4. Analyzed different input variables, including service time, waiting time, and people waiting versus days of the week to give insights of huge data used (which contained around 30,909 patients who were used in the training model).
5. Introduced a new technique for a new feature extracted (e. g., minute, hour, and day) from existing features (e. g., register, exam, and discharge time).

6.2.3 Lab Test Results (COVID-19) Prediction:

1. Developed a new machine learning model with multi-optimization algorithms (e.g., NN, SVR, LR, KNN, GBRT, ET, DT, and RF) to predict the waiting times of lab test results (COVID-19 data) based on predictive factors such as

receiving lab and sending facility.

2. Analyzed a huge amount of real-life data (comprised 54,730 patients) recorded during the pandemic, including patient age, gender, and nationality, as well as test status, result status (complete and rejected), receiving lab, result interpretation (positive and negative), date time required (the date that patient took the test), and result date time (the date of receiving the results).
3. Provided different metrics including MSR, MAE, RMSE, and R-Squared to achieve the outperformed model.
4. Provided examples involving decision on healthcare measurement of the COVID-19 tests process and the action needed to improve the service (e.g., increases in the centers or speed up the process) and proper prediction tools to prepare against possible threats and consequences for future waves of COVID-19.

Finally, based on experiments performed and models illustrated in this dissertation, all models provide a guideline for overcrowding and waiting time analysis, not only in healthcare but also in other sectors, considering model understandability, feature extraction processes, and use of medical data. Our models provide avenues for future research into the intelligent healthcare system with Internet of Things (IoT) and information gathering by embed the algorithms into the EHR environment.

6.3 Future Works

Many milestones and goals in this dissertation were achieved, but limitless possibilities in this work exist pushing us to reach more advances and extend this work. Our primary research vision included an intelligent queue where IoT and sensors could collect data of the system behaviors and embed our algorithm in a simulated Electronic Health Record (EHR) environment. Due to the many challenges such as smart object needed, cost of multiple sensors, appropriate platform to develop the models for such tasks, we plan to pursue it for future work.

Another significant future work, the DL model could be deployed as a web application to allow patients to join the queue prior. More analysis could be implemented in preprocessing step and data dimensional reduction for the provided models using Principal Components Analysis (PCA) with high dimensional correlated data at EHR.

In the near future, we plan to extend our analysis to include patient workflow analysis to reduce overall patient time and optimize the use of resources using reinforcement learning and control theory. This work will improve the patient's workflow by controlling the resource pool for triage and exam rooms in ERs. Moreover, we will use real traffic data to transferring non-emergency patients to other hospitals in multi-hospital settings using sources such as Google maps. Patient travel data could be added to healthcare waiting times. This strategy of transferring patients between hospitals can be used to minimize patient wait times without increasing the number of required resources.

APPENDIX A

RMSPROP, ADAM and ADAGRAD OPTIMIZATION ALGORITHMS RESULTS

Table A.1. Patient arrival time data (one day).

Day 1			
Patient	Arrival time	Waiting Time	Service Time
0	7:01	33	84
1	7:27	39	75
2	7:44	42	78
3	10:07	27	78
4	10:12	42	69
5	10:22	30	78
6	10:24	27	81
7	13:56	30	81
8	14:26	33	78
9	17:33	36	72
10	18:27	33	84
11	19:09	42	75
12	21:20	36	84
13	22:14	45	72
14	23:47	45	84
15	23:51	45	75

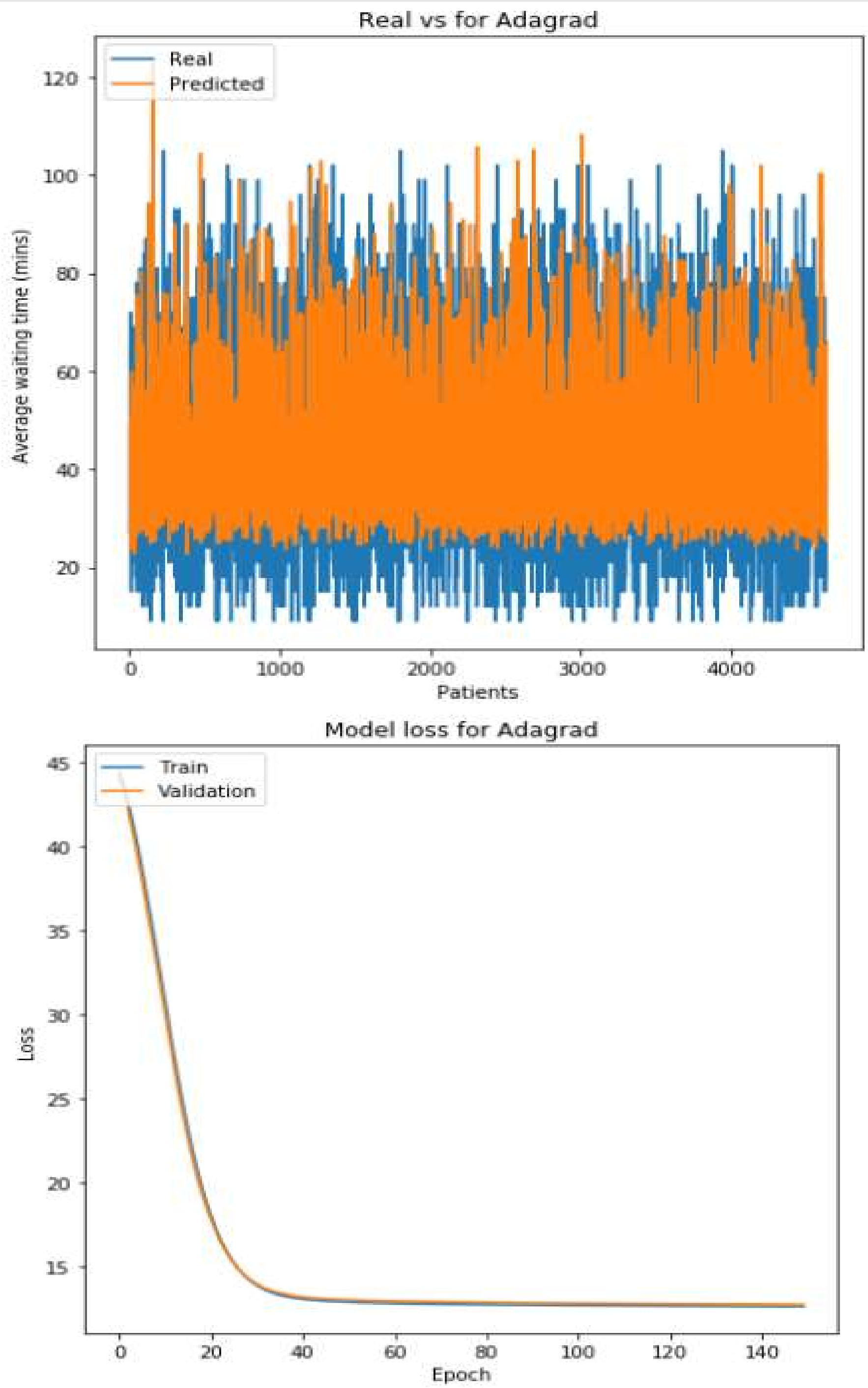

Figure A.1. Adagrd aptimation algorithm resutls (Waiting time predicted vs actual and plot of model loss on training and validation dataset).

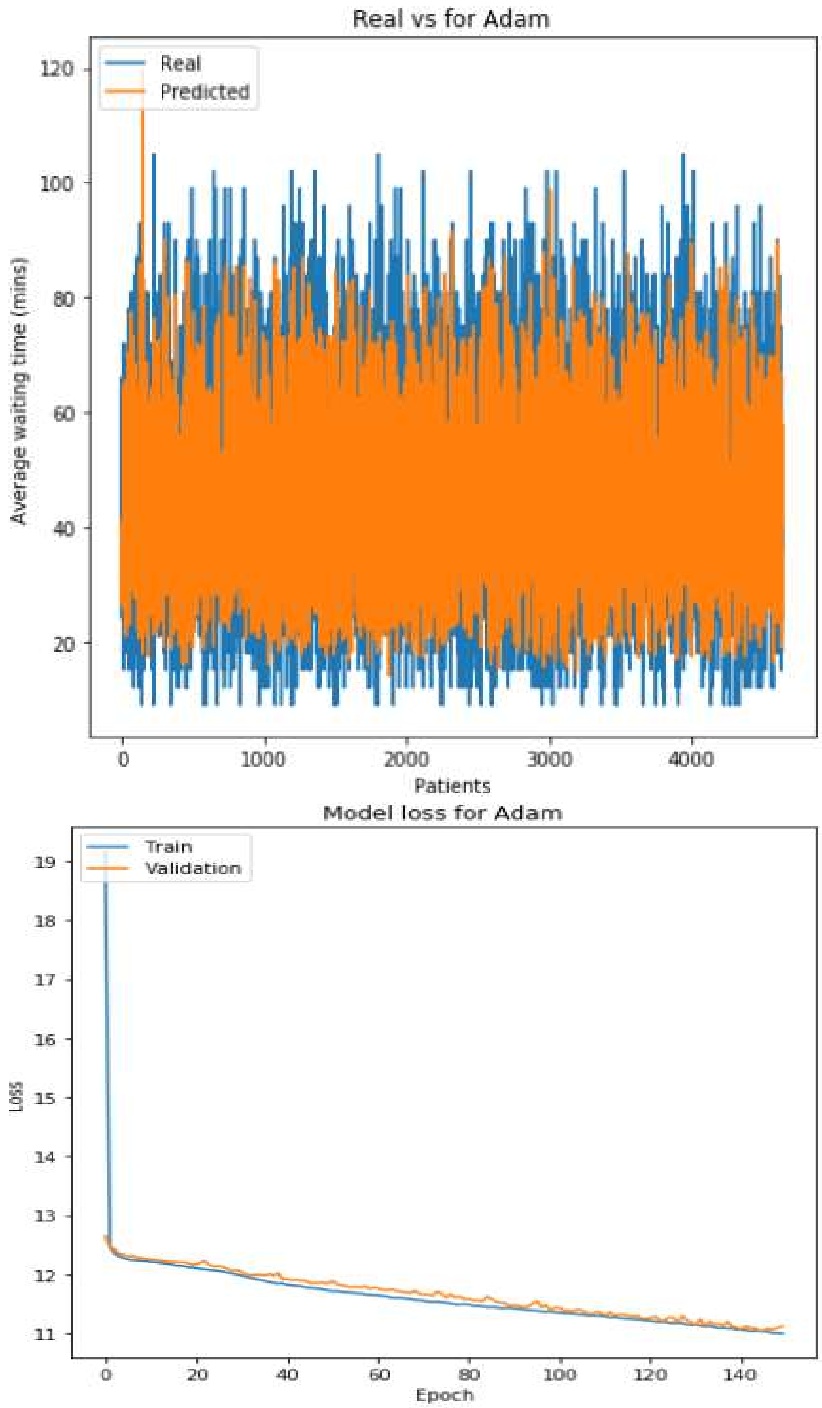

Figure A.2. Adam aptimation algorithm resutls (Waiting time predicted vs actual and plot of model loss on training and validation dataset).

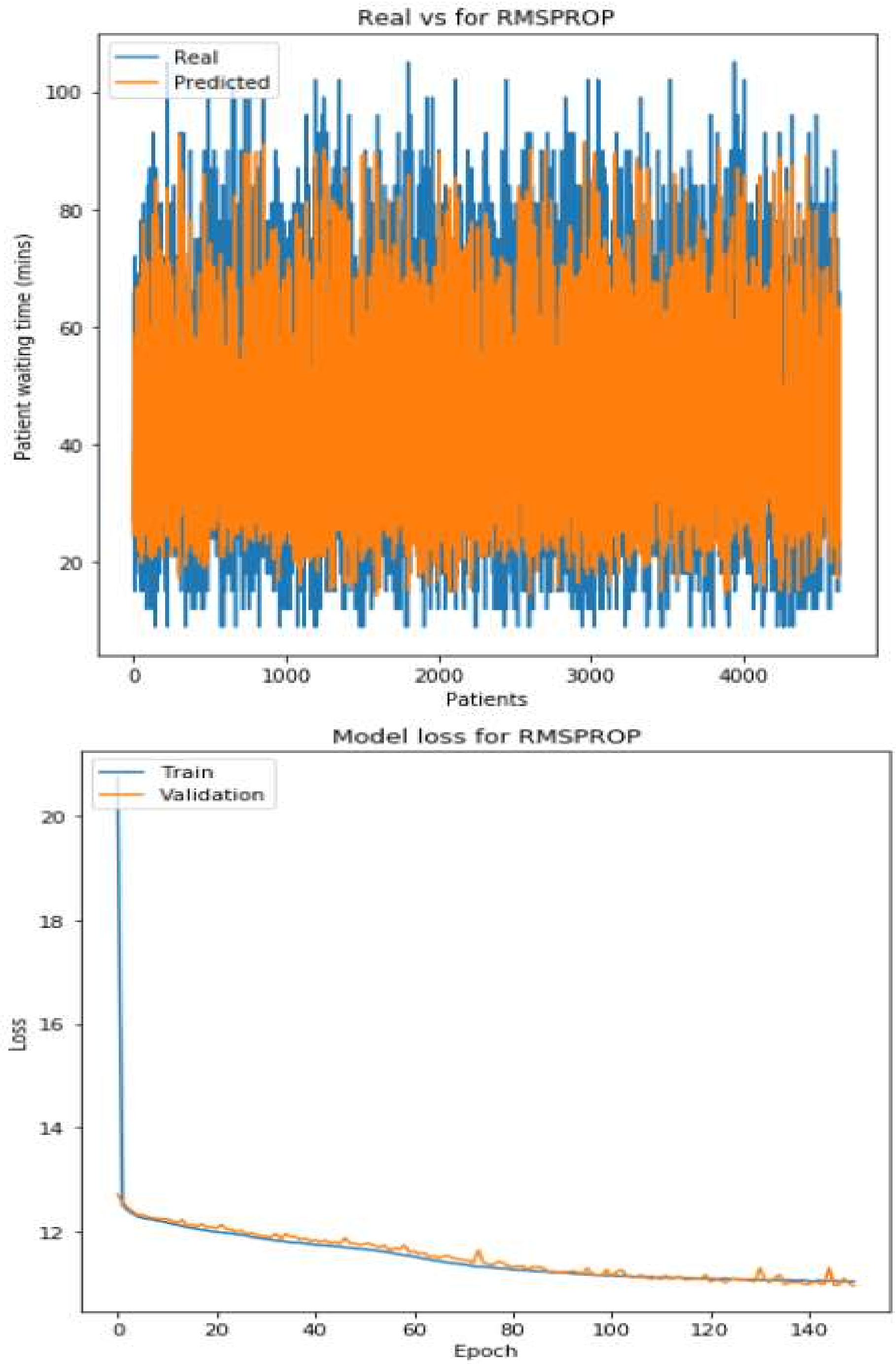

Figure A.3. RMSprop aptimation algorithm resutls (Waiting time predicted vs actual and plot of model loss on training and validation dataset).

APPENDIX B

EXPLORATORY ANALYSIS FOR LAB TEST DATA

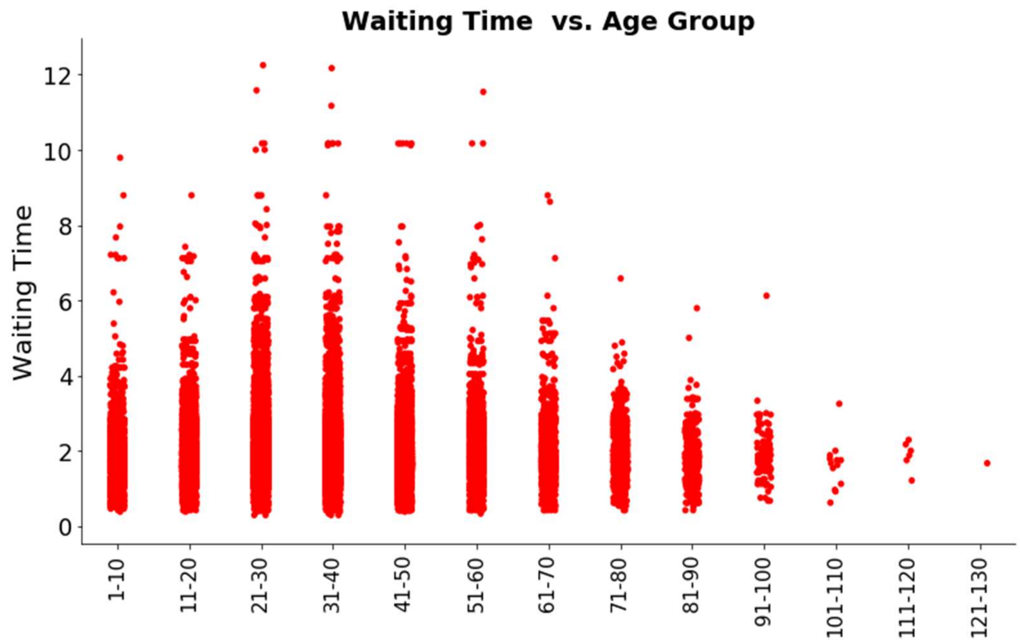

Figure B.1. Average waiting time Vs age group.

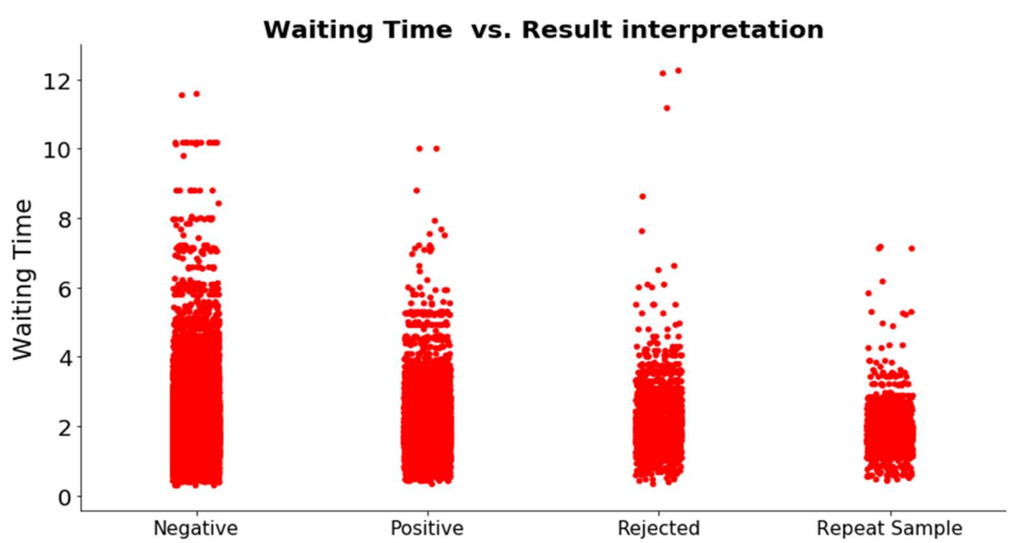

Figure B.2. Average waiting time Vs results interpretation.

APPENDIX C

THE FULL DECISION TREE AND DEPTH 2 IN DECISION TREE RESULTS

The whole tree:

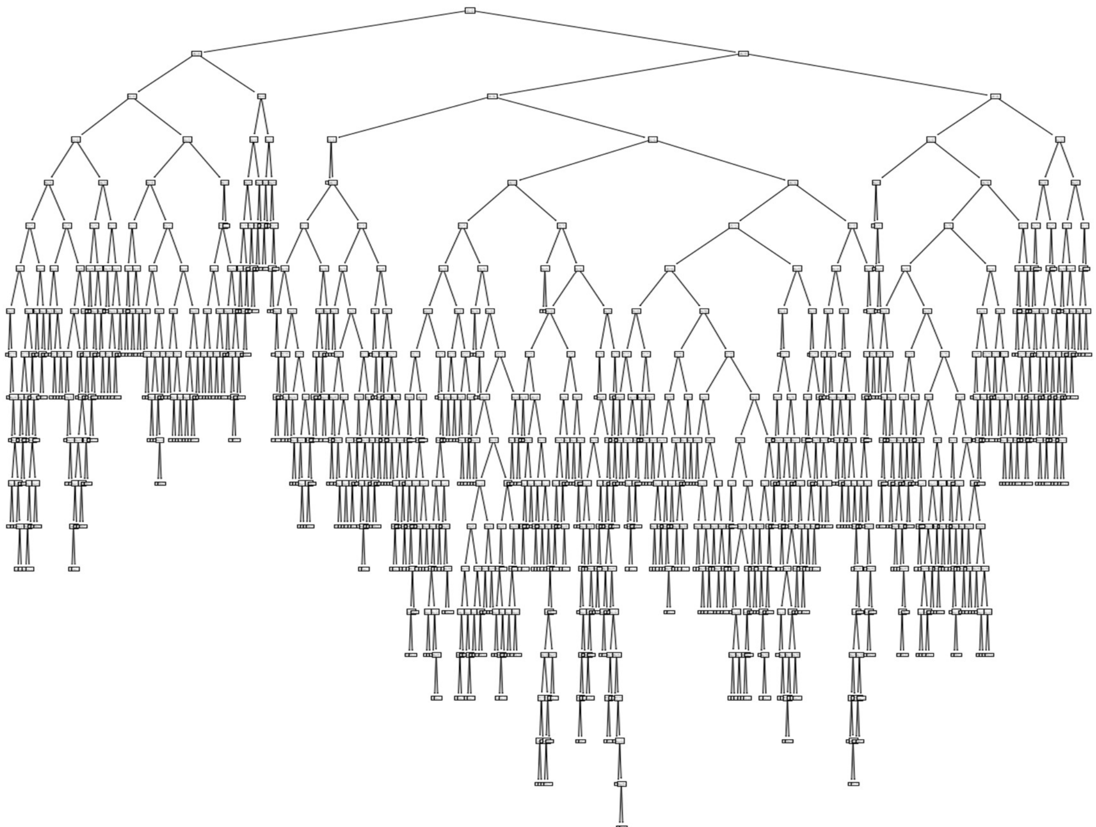

Figure C.1. Plot of full decision tree (1215 nodes).

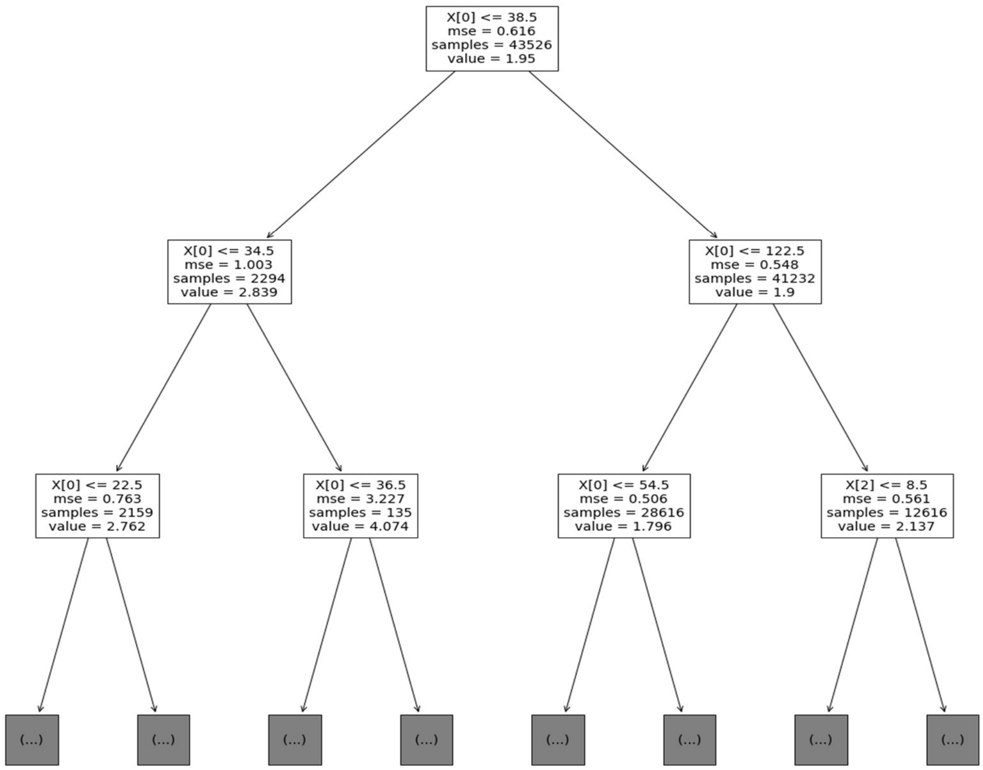

Figure C. 2. Plot of depth 2 in decision tree (7 nodes).

Where:
X[:, 0] -> Date

X[:, 1] -> Sending Facility

X[:, 2] -> Receiving Lab

APPENDIX D

CROSS-VALIDATION: EVALUATION ESTIMATOR PERFORMANCE OF DATA SPLIT

K-fold cross-validation (CV):

We used CV technique to avoid overfitting and hold out part of the available data as a test set X_test, y_test. As shown in figure D. 1, the process of K-fold where we partition our data set (randomly selected portions of the data) into training and test set. The test set (withhold set) kept separate from the training procedure. For example, in our case, the standard K-fold cross-validation, the training data is randomly partitioned into five partitions (or folds). Each partition is used to construct a regression model.

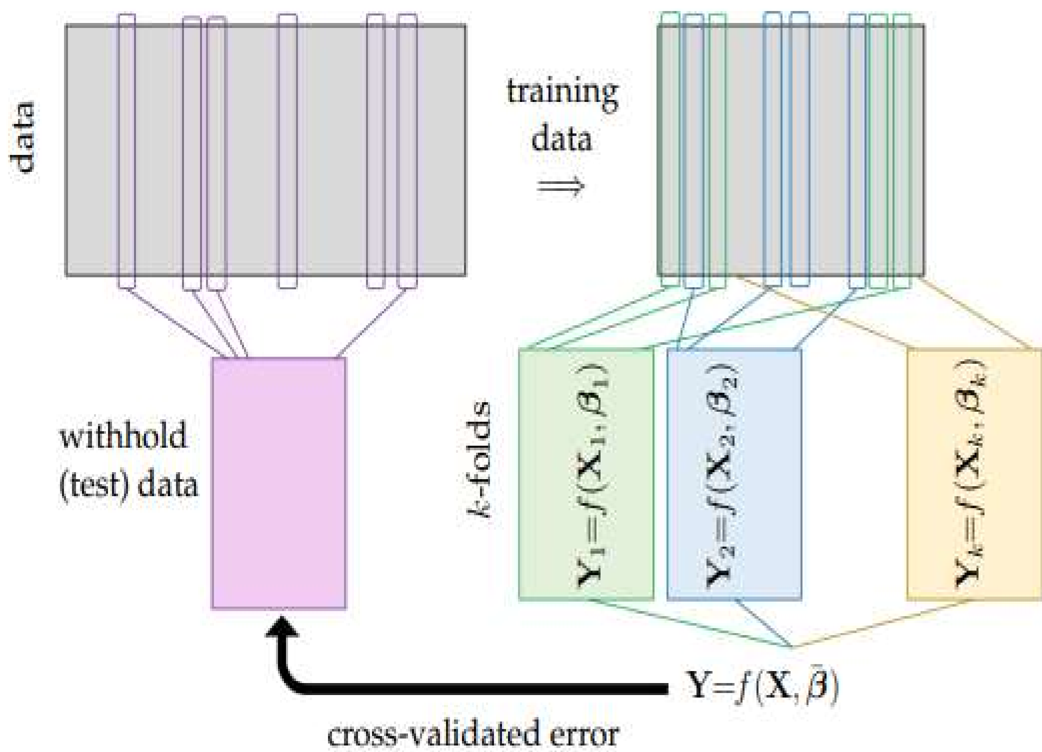

Figure D. 1. k-fold cross-validation technique [212].

APPENDIX E

MODELS INFORMATION: MACHINE, PROCESSOR, TOTAL TRAINING TIME AND MORE

Models' information was used, including the machine (PC) and the processor. Also, the model training total time for results to converge is shown in the figures below. Figure E. 1 represents the system information from the first experiment (Chapter 3), Figure E. 2 represents the second experiment system information (Chapter 4). Finally, Figure E. 3 represents the last experiment information (Chapter 5).

```
======================================== System Information_1st experiment ========================================
System: Windows
Node Name: DESKTOP-K5EJIHB
Release: 10
Version: 10.0.19041
Machine: AMD64
Processor: Intel64 Family 6 Model 61 Stepping 4, GenuineIntel
Total Training Time: 0.546 minutes
```

Figure E. 1. System information 1st experiment.

```
======================================== System Information ========================================
System: Windows
Node Name: DESKTOP-K5EJIHB
Release: 10
Version: 10.0.19041
Machine: AMD64
Processor: Intel64 Family 6 Model 61 Stepping 4, GenuineIntel
Total Training Time: 2.767 minutes
```

Figure E. 2. System information 2nd experiment.

```
====================================== System Information_Third experiment ======================================
System: Windows
Node Name: DESKTOP-K5EJIHB
Release: 10
Version: 10.0.19041
Machine: AMD64
Processor: Intel64 Family 6 Model 61 Stepping 4, GenuineIntel
Total Training Time: 4.346 minutes
```

Figure E. 3. System information 3rd experiment.

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