OUWB School of MEDICINE

OAKLAND UNIVERSITY WILLIAM BEAUMONT®

Using Deep Learning for Digital Subtraction Angiography Based Cerebral Aneurysm Detection and Rupture Risk Assessment

Yu Rim Park B.S.[1], Muhammad Irfan M.S.[2], Khalid Mahmood Malik Ph.D.[3], Ghaus Malik M.D.[4]

[1] Oakland University William Beaumont School of Medicine , [2] Department of Computer Science & Engineering, Oakland University , [3] Department of Computer Science, University of Michigan-Flint , [4] Department of Neurosurgery, Henry Ford Health System

Introduction

Accurate detection of intracranial aneurysms is critical due to the high mortality (30-day mortality rate of 44%[1]) associated with subarachnoid hemorrhage. There are multiple imaging modalities used for cerebral aneurysm detection including digital subtraction angiography (DSA), computed tomography angiography (CTA), and magnetic resonance angiography (MRA). The challenge lies in the visual similarities between vascular loops and aneurysms as demonstrated in Figure 1. This makes accurate segmentation difficult for not only physicians at times, but also machine learning techniques. Additionally, there are many variables to be considered including aneurysm size, location, and hemodynamics for prediction of aneurysm rupture. This has led to a larger focus on using deep learning for aneurysm detection using DSA[2], CTA[3], and MRA[4]. As far as aneurysm rupture risk prediction, there has not been as much research in development. Our team has preliminary work demonstrating that machine learning could be a viable approach for data to allow for clinical translation. Our project rupture prediction, but there has been a need for improved accuracy and reliability in both segmentation and the analysis of this aims to improve the detection and segmentation of intracranial aneurysms using two-dimensional (2D)- DSA, and to assess aneurysm rupture risk by overcoming the issue of lack of depth inherent to 2D imaging.

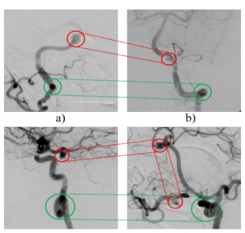

Figure 1. DSA image with green circles indicating loops and red circles indicating aneurysms, demonstrating the complexity in distinguishing one from another.

Aims and Objectives

- To develop a fusion model with features and deep learning models to improve intracranial aneurysm segmentation and detection.
- To incorporate the above model in a convolutional neural network (CNN) which can predict the rupture risk of the aneurysm.

Methods

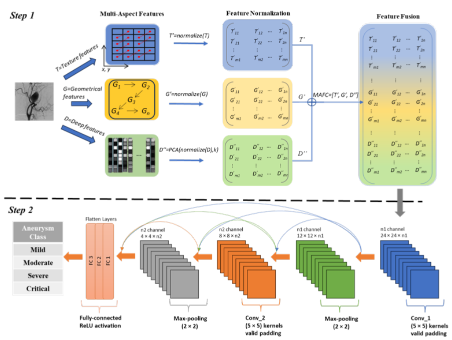

Figure 2. Flowchart illustrating the proposed method of extraction of features, fusion of normalized features, and conversion into a CNN for risk classification.

Deep learning models such as VGG and ResNet are highly performant in image classification. However, these models are still unable to meet our classification need. To supplement these models, we have extracted additional geometric features with the help of the U-Net model, as well as using Tamura features to provide texture features for our images.

Each of these feature sets are important in the task of aneurysm detection, so we have devised a method called Multi-Aspect Feature Concatenation (MAFC) which helps integrate the distinct characteristics of each feature set, while maintaining the unique information from each.

Following feature extraction, each set is normalized, and the most important deep features are extracted through Principal Component Analysis. The final feature set is simply the normalized texture features, geometric features, and dimensionality-reduced deep features.

To classify aneurysms by their risk of rupture, we have used a fully-connected convolutional neural network with the MAFC features as an input layer, multiple hidden layers, and an output layer. The hidden layers allow the model to learn complex relationships within the input data and provide a prediction for the risk severity (mild, moderate, severe, critical) for a given aneurysm case.

A total of 569 DSA images from Henry Ford Health Systems were used for testing the clinical applicability of the proposed system for rupture prediction. All images were first annotated by neurosurgery residents and attending, who classified the given set of images into the four categories.

Results

We trained and tested a series of CNN models on different combinations of VGG and ResNet features and evaluated model performance. The fusion model surpassed the individual models in terms of accuracy, sensitivity, specificity, precision, and F1-score, as shown in Table 1. Similar ablation study was conducted for different combinations of CNN model.

Table 1. Ablation study on selection of various deep features for aneurysm detection

Features	Accuracy	Sensitivity	Specificity	Precision	F1-Score
VGG	0.85	0.78	0.91	0.82	0.80
ResNet	0.87	0.80	0.93	0.87	0.83
Fusion of both	**0.92**	**0.87**	**0.96**	**0.91**	**0.89**

We also investigated the impact of each feature set for aneurysm risk analysis. Table 2 shows that the combination of all characteristics is significantly more effective than any individual feature set. The Deep Features have the second-best performance, followed by Geometrical Features and First-Order Features. These results suggest that the fusion of multiple types of features can improve the performance of a classifier for the classification of aneurysm rupture.

Table 2. Impact of different features on aneurysm risk analysis

Features	ACC	P	R	F	AUC
Deep Features	0.78	0.79	0.77	0.77	0.85
Texture Features	0.71	0.72	0.69	0.69	0.77
Geometrical Features	0.72	0.73	0.71	0.70	0.79
Fusion of all features	**0.87**	**0.88**	**0.87**	**0.87**	**0.94**

Lastly, we evaluated the performance of the proposed CNN model against current classifiers. Table 3 shows that the CNN model outperforms all six classifiers across all performance metrics. The CNN network achieves an accuracy of 94%, significantly higher than the accuracy of the best performing classifier, Random Forest, at 88%. Similarly, the CNN network surpasses the corresponding best-performing classifier in terms of accuracy, recall, F-1 score, and AUC score.

Table 3. Evaluation of CNN and existing classifiers for aneurysm risk analysis

Classifier	ACC	P	R	F-1 Score	AUC
Logistic Regression	0.85	0.86	0.83	0.84	0.91
Decision Tree	0.79	0.78	0.81	0.79	0.82
Random Forest	0.88	0.90	0.87	0.88	0.94
Naive Bayes	0.81	0.82	0.78	0.79	0.88
KNN	0.76	0.74	0.79	0.76	0.81
SVM	0.87	0.88	0.86	0.87	0.92
CNN	**0.95**	**0.95**	**0.94**	**0.95**	**0.98**

Conclusions

Our results suggest that utilizing a fusion of different features leads to an improved performance in aneurysm rupture risk analysis using 2D DSA imaging. We also found that the model used in our proposed pipeline outperforms several well-established traditional machine learning algorithm across various metrics. Because deep learning is capable of automatically learning intricate features and patterns from complex datasets, it confers an advantage over traditional machine learning methods when tackling a complex task such as rupture risk prediction.

Despite the effective performance of the proposed method, there are certain limitations. Namely, we cannot determine the generalizability of our method since we only used in-house dataset given that no publicly available dataset exists. Furthermore, while we used the geometrical, deep, and texture features that are most commonly used in medical image analysis, there may be other relevant features, such as solidity, symmetry, convexity and roundness of the aneurysm, that were not included in the analysis of our study. It is possible that the performance of the model may be improved by incorporating these features or other morphological and intensity-based features.

In summary, given that intracranial aneurysms can potentially lead to devastating consequences, it is critical to identify and treat those that carry a high risk of rupture. Determining rupture probability is a complex task due to the influence of a multitude of factors. An AI-based rupture risk prediction tool that can effectively integrate multiple features in its analysis can assist healthcare professionals in making informed clinical decisions and should be further researched.

References

1. Pobereskin LH. Incidence and outcome of subarachnoid haemorrhage: a retrospective population based study. *J Neurol Neurosurg Psychiatry.* 2001;70(3):340-343. doi:10.1136/jnnp.70.3.340
2. Shi Z, Miao C, Schoepf UJ, et al. A clinically applicable deep-learning model for detecting intracranial aneurysm in computed tomography angiography images. *Nat Commun.* 2020;11(1):6090. Published 2020 Nov 30. doi:10.1038/s41467-020-19527-w
3. Yang J, Xie M, Hu C, et al. Deep Learning for Detecting Cerebral Aneurysms with CT Angiography. *Radiology.* 2021;298(1):155-163. doi:10.1148/radiol.2020192154
4. Nakao T, Hanaoka S, Nomura Y, et al. Deep neural network-based computer-assisted detection of cerebral aneurysms in MR angiography. *J Magn Reson Imaging.* 2018;47(4):948-953. doi:10.1002/jmri.25842