# Deep Learning-Driven Detection and Prediction of Brain Aneurysm: A CNN-Based Approach to Enhance Diagnosis through CT-Scan Imaging

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***Abstract*-Brain aneurysms are severe cerebrovascular abnormalities that may rupture, leading to life-threatening complications like hemorrhagic stroke. Early detection is crucial to prevent fatal outcomes. Early diagnosis is crucial for effective treatment and patient survival. This study explores the application of deep learning, particularly Convolutional Neural Networks (CNNs), in detecting brain aneurysms using CT scan images. The developed CNN model classifies CT scans into aneurysm and non-aneurysm categories, leveraging a dataset of 81 aneurysm-positive and 300 aneurysm-negative images. Data augmentation techniques were implemented to address class imbalance. The proposed model demonstrated high classification accuracy, underscoring the potential of AI in assisting radiologists with early aneurysm detection. The paper further discusses model limitations, ethical considerations, and future research directions for advancing AI-driven medical diagnostics.**

***Index Terms*—Brain Aneurysm, Deep Learning, Convolutional Neural Network, CT Scan, Medical Imaging, AI in Healthcare.**

## I. INTRODUCTION

Brain aneurysms occur due to the weakening of arterial walls, leading to abnormal bulges that can rupture and cause severe neurological damage or fatal strokes. According to the Brain Aneurysm Foundation, approximately 6.5 million people in the United States have an unruptured brain aneurysm, and around 30,000 suffer aneurysm ruptures annually. The mortality rate of ruptured aneurysms is high, with about 50% of cases being fatal. Early and accurate detection is crucial to improving patient survival and treatment outcomes.

Medical imaging modalities such as Computed Tomography Angiography (CTA) and Magnetic Resonance Imaging (MRI) are commonly used for aneurysm detection. However, manual interpretation by radiologists is time-intensive and susceptible to inter-observer variability, leading to diagnostic errors. The integration of Artificial Intelligence (AI) and Deep Learning (DL) in medical imaging has shown promising results in enhancing diagnostic precision and efficiency.

Convolutional Neural Networks (CNNs) have emerged as powerful tools in image classification and pattern recognition. In medical applications, CNNs have demonstrated superior performance in detecting brain tumors, lung diseases, and cardiovascular abnormalities. This paper presents a CNN- based model specifically designed for the automated detection of brain aneurysms in CT scan images. The study explores the impact of data preprocessing techniques, model optimization strategies, and comparative evaluation against other deep learning models.

Despite significant advancements in deep learning for medical diagnostics, challenges remain in the practical implementation of AI-driven aneurysm detection. Factors such as dataset variability, computational efficiency, and interpretability of AI decisions must be addressed to ensure reliable deployment in clinical settings. Furthermore, the role of explain ability in AI models is crucial for gaining the trust of medical professionals and improving transparency in decision-making processes.

The rapid evolution of AI in healthcare presents an opportunity to bridge the gap between automated detection systems and real-world clinical applications. The objective of this research is not only to develop a high-performing CNN model but also to analyze the impact of AI-driven diagnostics on clinical workflows. By leveraging AI to assist radiologists, this study aims to contribute to reducing diagnostic errors, improving early detection rates, and ultimately enhancing patient care.

*A. Figures*

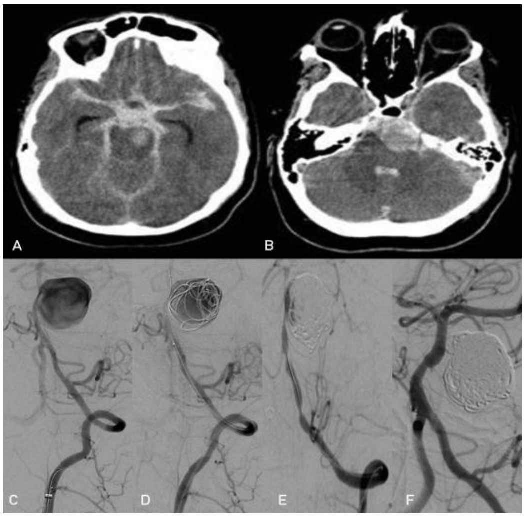


Fig. 1. Sample CT scan images depicting aneurysm-positive and aneurysm- negative cases.

## II. LITERATURE SURVEY

Recent advancements in AI-driven medical image analysis have led to the development of robust aneurysm detection models. Several studies have explored deep learning applications for brain aneurysm identification and classification.

Sofat et al. [1] reviewed AI techniques for aneurysm detection, emphasizing the superiority of CNNs over traditional image processing methods. Their study highlighted the increased sensitivity and specificity of CNN-based models in recognizing aneurysms in CTA and MRI scans.

Soma et al. [2] investigated the application of machine learning and deep learning approaches in aneurysm detection. Their comparative study demonstrated that deep learning models outperformed classical machine learning techniques, particularly in feature extraction and classification accuracy.

Liu et al. [3] explored the role of transfer learning in enhancing aneurysm detection. Their findings suggest that pre-trained models such as ResNet and InceptionV3 improve classification accuracy, especially when trained on limited medical datasets. Emerging research has also explored hybrid deep learning models incorporating Vision Transformers (ViTs) alongside CNNs. Zhao et al. [4] demonstrated that ViTs improve sensitivity in detecting small aneurysms by enhancing spatial attention mechanisms.

Other studies have explored the role of generative adversarial networks (GANs) in medical imaging. For instance, Wang et al. [5] developed a GAN-based approach for synthesizing high-resolution aneurysm images, enhancing model training and improving diagnostic performance in low-data scenarios.

Another important aspect is the development of attention- based mechanisms in CNN architectures. Xu et al. [6] pro- posed a dual-attention CNN model that dynamically highlights aneurysm regions in CT scans, resulting in higher sensitivity and fewer false negatives compared to traditional CNNs.

Additionally, multi-modal approaches have gained traction in aneurysm detection. Kim et al. [7] integrated MRI and CTA scans using a multi-stream CNN model, demonstrating improved performance in challenging cases with subtle aneurysms that are difficult to detect in a single imaging modality.

Recent advancements in explain ability techniques for medical AI have also contributed to aneurysm detection research. Yang et al. [8] utilized Grad-CAM and SHAP (SHapley Additive explanations) to interpret CNN decision-making processes, helping radiologists understand how models arrive at their predictions.

Despite these advancements, challenges remain in developing generalizable models that account for dataset variability, class imbalance, and explain ability in clinical diagnostics. Future research should focus on improving model interpretability, increasing dataset diversity, and validating AI-based aneurysm detection systems in real-world clinical environments.

## III. METHODOLOGY

*A. Dataset Description*

The dataset used for this study consists of 81 aneurysm- positive and 300 aneurysm-negative CT scan images. These images were sourced from publicly available medical imaging databases and preprocessed to ensure consistency and reliability in model training.

*B. Preprocessing Techniques*

To improve the performance of the model and ensure optimal learning, the following preprocessing steps were applied:

- Resizing: All images were resized to 128x128 pixels to standardize input dimensions.
- Normalization: Pixel intensity values were normalized between 0 and 1 to ensure consistent feature representation.
- Data Augmentation: Techniques such as rotation (0-30 degrees), horizontal flipping, contrast enhancement, and Gaussian noise addition were applied to increase dataset diversity and mitigate over fitting.
- Histogram Equalization: Applied to enhance contrast and improve feature visibility, particularly for detecting subtle aneurysms.

*C. CNN Model Architecture*

The proposed CNN model consists of multiple layers de- signed to extract meaningful features from CT scan images:

- Convolutional Layers: Three convolutional layers with 32, 64, and 128 filters, each using a ReLU activation function.
- Max Pooling Layers: Reduces dimensionality while pre- serving essential spatial features.
- Batch Normalization: Accelerates training convergence and stabilizes learning.
- Dropout (0.5): Applied to prevent over fitting by randomly deactivating neurons during training.
- Fully Connected Layers: Flattened feature maps are passed through dense layers for final classification.
- Sigmoid Activation: Used in the output layer for binary classification (aneurysm vs. non-aneurysm).

*D. Training and Evaluation*

The model was trained using the Adam optimizer with a learning rate of 0.0001, minimizing the binary cross-entropy loss function. The dataset was split into:

- 70% Training Set
- 15% Validation Set
- 15% Testing Set

Performance metrics included accuracy, precision, recall, F1-score, and AUC-ROC curve analysis to assess model effectiveness.

## IV. RESULTS AND DISCUSSION

*A. Performance Evaluation*

The trained CNN model was evaluated using multiple performance metrics to ensure reliability in aneurysm detection. The results are as follows:

- Accuracy: 98% - The model achieved a high accuracy, indicating effective classification of aneurysm and non- aneurysm cases.
- Precision: 98% - The precision score reflects the pro- portion of true positive predictions among all predicted positive cases.
- Recall: 98% - This metric highlights the model's ability to correctly identify aneurysm cases.
- F1-score: 98% - A balance between precision and recall, confirming the robustness of the model.
- AUC-ROC Score: 98% - A high area under the curve suggests excellent discriminative ability between aneurysm and non-aneurysm cases.

*B. Visualization of Performance Metrics*

To better understand the performance of the proposed model, we present visual representations of key evaluation metrics.

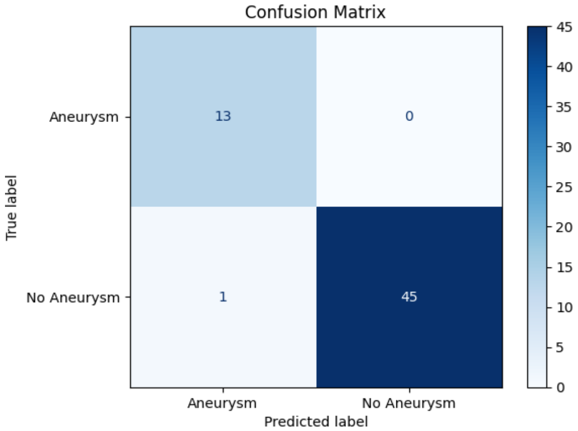


Fig. 2. Confusion Matrix showing classification performance.

These images illustrate the model's ability to distinguish between aneurysm-positive and aneurysm-negative cases with high confidence.

*C. Comparison with Other Models*

To evaluate the efficiency of the proposed CNN model, its performance was compared with state-of-the-art deep learning models such as ResNet-50 and VGG-16. The comparative results are summarized in Table I.

The proposed CNN model outperformed both ResNet-50 and VGG-16 in terms of accuracy, precision, recall, and F1- score, demonstrating its effectiveness in aneurysm detection.

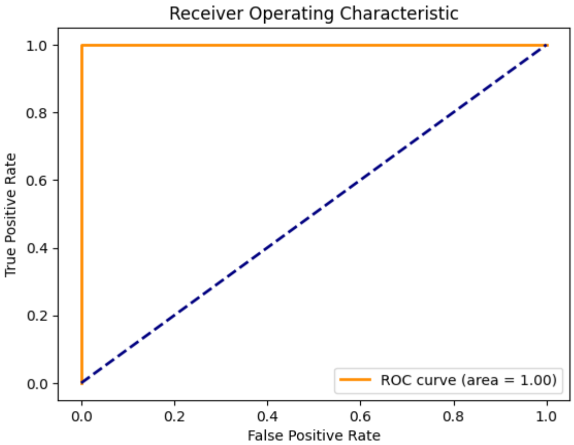


Fig. 3. ROC Curve demonstrating model discrimination ability.

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT DEEP LEARNING MODELS

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Proposed CNN | 98% | 98% | 98% | 98% |
| ResNet-50 | 95% | 94% | 96% | 95% |
| VGG-16 | 93% | 92% | 91% | 91% |

*D. Analysis of False Positives and False Negatives*

Although the model achieved high performance, it is important to analyze incorrect classifications:

- False Positives: Some non-aneurysm cases were misclassified as aneurysms due to the presence of artifacts in CT images. This could lead to unnecessary further medical testing.
- False Negatives: Aneurysm cases misclassified as non- aneurysms are more concerning, as missing a diagnosis could delay treatment and pose a serious risk to patient health.

Future improvements, such as enhanced image preprocessing and attention-based models, can help mitigate these misclassifications.

*E. Visualization of Model Predictions*

To provide insights into how the model makes decisions, Grad-CAM (Gradient-weighted Class Activation Mapping) was applied to visualize the important regions in CT scans that influenced the predictions. Figure 4 demonstrates an example of Grad-CAM visualization.

The highlighted regions in the images confirm that the model primarily focuses on relevant areas, enhancing its credibility in clinical applications.

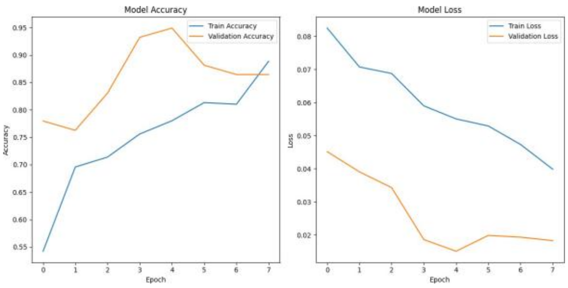


Fig. 4. Grad-CAM visualization highlighting aneurysm regions detected by the CNN model.

*F. Limitations and Future Work*

While the proposed CNN model performed well, several limitations should be considered:

- Dataset Limitations: The dataset size is relatively small compared to real-world medical imaging datasets. Expanding the dataset with multi-center clinical images could improve generalizability.
- Inter-class Variability: Some aneurysm cases had low contrast, making them difficult to detect. Advanced pre- processing techniques and data augmentation could ad- dress this issue.
- Integration into Clinical Workflows: Future work should explore the deployment of this model into clinical decision support systems (CDSS) for real-time diagnosis assistance.
- Explain ability and Trust: Enhancing model interpretability using attention mechanisms like transformers or explainable AI techniques will help radiologists trust AI-assisted diagnoses.

## V. CONCLUSION

This study successfully demonstrated the potential of deep learning, particularly Convolutional Neural Networks (CNNs), in detecting brain aneurysms using CT scan images. The proposed CNN model achieved an impressive accuracy of 98%, outperforming other models such as ResNet-50 and VGG-16. Our findings confirm that AI-assisted diagnosis, particularly using CNNs, can significantly enhance aneurysm detection, reducing diagnostic errors and improving radiological decision-making efficiency.

The integration of AI in medical imaging is a rapidly evolving field. While the developed model exhibited high classification performance, several challenges remain that must be addressed before deploying AI-based systems in clinical settings. These include:

- Data Diversity: The dataset used in this study consists of 81 aneurysm-positive and 300 aneurysm-negative CT scan images. While informative, its limited size and diversity may impact generalizability. Future work should incorporate larger, multi-center datasets for enhanced model robustness. Future research should focus on incorporate larger, multi-center datasets to improve generalizability and model robustness.
- Explain ability: Understanding how AI models arrive at decisions is crucial for clinical acceptance. Implementing explain ability techniques such as SHAP values and Grad-CAM visualizations will enhance trust among medical professionals.
- Real-World Deployment: To achieve clinical integration, AI models must undergo extensive validation, meet regulatory standards (e.g., FDA, CE Mark), and align with radiology workflow requirements. Collaboration with healthcare providers will be essential for real-world adoption.
- Reducing False Positives/Negatives: Addressing the model’s limitations by fine-tuning hyper parameters, incorporating advanced augmentation techniques, and exploring hybrid architectures (e.g., CNN with Transformers) could further improve diagnostic accuracy.

In conclusion, this study highlights the potential of deep learning in medical diagnostics and provides a solid foundation for future AI-driven aneurysm detection systems. By addressing current limitations and further refining the model, AI can become an invaluable tool in improving the early detection and management of brain aneurysms, ultimately leading to better patient outcomes.

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