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Innovations in Stroke Identification A Machine Learning-based Diagnostic Model using Neuroimages

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***Abstract*— The proposed Stroke Classification System is an AI-driven diagnostic support tool developed to assist clinicians in the timely detection of stroke using brain MRI images. The framework adopts a hybrid architecture that combines the deep feature extraction capability of VGG16 with the robust classification performance of XGBoost to accurately distinguish between stroke and non-stroke cases. Experimental evaluation demonstrates a precision of 97.5% under controlled conditions, highlighting its reliability for clinical assistance.To ensure practical usability, the system is deployed as a web application using Flask, enabling healthcare professionals to upload MRI scans and receive near real-time diagnostic predictions. The platform supports rapid inference, maintains diagnostic history, and is designed for scalable deployment on cloud services such as AWS and Heroku. By integrating accuracy, speed, and accessibility, the system serves as an efficient and user-friendly AI solution for stroke diagnosis support.**

***Index Terms*— Stroke Detection, Brain MRI, Deep Learning, VGG16, XGBoost, Flask, Image Classification, Medical Imaging, Real-Time Prediction, AI in Healthcare.**

I. INTRODUCTION

Stroke remains one of the leading causes of mortality and long-term disability worldwide, posing a significant burden on healthcare systems and societies. Rapid and accurate diagnosis is critical, as timely intervention can substantially reduce neurological damage and improve survival rates. However, conventional stroke diagnosis primarily depends on expert interpretation of neuroimaging scans, particularly Magnetic Resonance Imaging (MRI). Although MRI-based assessment is highly informative, it is often time-consuming, resource-intensive, and dependent on specialist availability. In emergency scenarios, delays in interpretation may negatively affect patient outcomes, especially in regions with limited access to experienced radiologists.

Recent advancements in artificial intelligence (AI) have transformed the landscape of medical imaging analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable capability in extracting complex spatial patterns from medical images. Among these architectures, VGG16 has proven effective in transfer learning scenarios, enabling robust feature extraction even when trained on relatively limited medical datasets. While CNN-based classifiers are powerful, integrating them with advanced machine learning algorithms can further enhance classification performance and stability.

An intelligent stroke classification framework can assist clinicians by analyzing brain MRI images and distinguishing between stroke-positive and non-stroke cases.

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Deep convolutional networks such as VGG16 are effective in extracting high-level spatial features from medical images, capturing structural and textural variations associated with stroke. These extracted features can be further processed using ensemble-based algorithms like XGBoost, which enhance classification performance through optimized decision modeling and reduced overfitting.

Beyond prediction accuracy, interpretability and usability are essential for real-world clinical adoption. Visual explanation techniques help highlight the brain regions that influence diagnostic decisions, increasing transparency and trust. Integration into a web-based environment enables healthcare professionals to upload MRI scans and receive near real-time results, supporting faster decision-making within hospital workflows. Scalability through cloud deployment further ensures accessibility across diverse healthcare settings.

Extensive experimentation on a balanced MRI dataset demonstrates that the proposed hybrid model achieves high accuracy, strong precision and recall, and stable generalization across varying imaging conditions. The system maintains fast inference times, making it suitable for near real-time clinical assistance. By combining diagnostic accuracy, computational efficiency, explainability, and deployability, this work contributes toward bridging the gap between AI research and practical healthcare implementation.

II. Literature Survey

Saritha et al. (2013) [1] investigated MRI brain image classification using wavelet entropy features combined with probabilistic neural networks. Their method focused on extracting handcrafted statistical features from MRI scans to differentiate abnormal brain tissues. While the approach demonstrated promising classification performance, its dependency on manually engineered features limited scalability and robustness across varying imaging conditions. With the advancement of deep learning, convolutional neural networks (CNNs) began replacing traditional feature extraction techniques. Bacchi et al. (2020) [2] applied deep learning models to predict functional outcomes in ischemic stroke patients undergoing thrombolysis. Their work demonstrated that CNN-based architectures could automatically learn discriminative spatial representations from neuroimaging data. However, performance was influenced by dataset size and diversity, highlighting the need for improved generalization strategies.

Yang et al. (2021) [3] utilized large-scale medical datasets and machine learning algorithms for stroke prediction in hypertensive patients. Their ensemble-based approach achieved high predictive accuracy by integrating multiple machine learning techniques. Although effective, the model focused more on structured clinical data rather than direct MRI image analysis.

Chun et al. (2021) [4] conducted a large prospective cohort study using machine learning models for stroke risk prediction. Their study demonstrated that AI models can assist in early risk stratification using demographic and clinical parameters. However, the work emphasized predictive modeling from tabular data rather than imaging-based classification.

Ntaios et al. (2021) [5] developed a machine learning-derived cardiovascular risk stratification model for ischemic stroke patients. The study emphasized interpretability and clinical applicability, highlighting the importance of transparency in AI-driven healthcare systems. Interpretability remains a crucial requirement for diagnostic support tools.

Uchida et al. (2022) [6] introduced a machine learning-based triage system for real-time stroke prediction in emergency settings. Their work focused on rapid decision-making and deployment readiness, demonstrating that AI models can assist clinicians during prehospital evaluation. However, the study did not deeply integrate convolutional feature extraction with optimized boosting classifiers.

More recent studies have explored hybrid architectures that combine deep learning with advanced ensemble methods. Saleem et al. (2024) [7] proposed a machine learning-based diagnostic model using neuroimages and demonstrated the effectiveness of combining optimized deep learning frameworks with structured classification strategies. Hybrid approaches showed improved robustness and classification stability compared to standalone CNN classifiers.

III. Proposed Method

A. Dataset Acquisition and Preprocessing

For the development of the automated brain stroke detection system, a structured and well-balanced dataset of brain MRI scans was collected from a publicly available medical imaging repository on Kaggle. The dataset consisted of two primary categories: stroke-affected cases and neurologically normal cases. Special attention was given to maintaining class balance to prevent model bias toward a dominant category.

Each MRI image underwent a standardized preprocessing pipeline to ensure uniformity and compatibility with the deep learning architecture. Initially, all images were converted to grayscale format to focus on structural brain patterns rather than color variations. Subsequently, every image was resized to 224 × 224 pixels, matching the input dimension requirement of the VGG16 architecture.

The dataset included MRI scans captured under varied clinical conditions, incorporating differences in orientation, intensity levels, contrast distribution, and axial slice representation. Such diversity allowed the model to learn generalized patterns rather than memorizing specific image characteristics.

To enhance model robustness and reduce overfitting, extensive data augmentation strategies were applied during training. These transformations included:

- Controlled image rotations
- Horizontal flipping
- Zoom scaling
- Brightness and contrast adjustments
- Minor translations and shifts

These augmentation techniques artificially expanded the effective training dataset size while preserving medically meaningful patterns. The complete dataset contained over 5,000 MRI images, evenly distributed between stroke and non-stroke categories. Each image was labeled according to verified diagnostic reports to ensure annotation reliability.

B. System Architecture and Implementation

The proposed system follows a hybrid deep learning and machine learning approach combining convolutional feature extraction with gradient boosting classification.

Feature Extraction using VGG16

A pre-trained VGG16 convolutional neural network was employed as a feature extractor. Transfer learning was adopted to leverage the spatial pattern recognition capability learned from large-scale image datasets. The top classification layers of VGG16 were removed, retaining only the convolutional base responsible for extracting hierarchical image features. The MRI images passed through the convolutional layers to generate high-dimensional feature representations capturing structural irregularities, lesion regions, and texture variations. The extracted feature maps were flattened into feature vectors, forming the input to the secondary classification stage.

Classification using XGBoost

Instead of using a traditional dense neural network classifier, the flattened feature vectors were fed into an Extreme Gradient Boosting (XGBoost) classifier.XGBoost was selected due to high computational efficiency, Strong generalization ability,Built-in regularization mechanisms, Capability to handle high-dimensional feature spaces.

The classifier was trained for binary classification (Stroke vs Non-Stroke). This hybrid combination allowed the system to benefit from deep spatial learning (VGG16) and robust decision-boundary optimization (XGBoost).

Implementation Environment

The proposed stroke detection system was developed using Python as the primary programming language due to its extensive support for machine learning and medical image processing frameworks. Deep learning operations, including convolutional feature extraction and model customization, were implemented using TensorFlow and Keras. These libraries enabled efficient utilization of transfer learning techniques with the VGG16 architecture. Image preprocessing tasks such as resizing, grayscale conversion, normalization, and enhancement were carried out using OpenCV, while NumPy was employed for handling multidimensional arrays and performing numerical computations.

TABLE I: REPRESENTS PYTHON LIBRARIES USED IN THIS RESEARCH WORK TO GET ACCURATE RESULTS; VARIOUS LIBRARIES ARE SHOWN

Library	Description
TensorFlow	Core deep learning framework for training and deploying VGG16
OpenCV	Image processing and enhancement (resizing, grayscale conversion)
NumPy	Numerical operations and array manipulation
scikit-learn	Validation splitting, evaluation metrics, and model utilities
Flask	Backend framework handling API and prediction routing
Matplotlib	Visualization tools for plotting and result interpretation
XGBoost	Gradient-boosted classifier for stroke vs. non-stroke prediction

For dataset partitioning, cross-validation, and performance evaluation, Scikit-learn utilities were integrated into the workflow. The final classification stage was implemented using XGBoost, which provided efficient gradient boosting–based decision learning on extracted deep features. To transform the trained model into a usable diagnostic tool, Flask was used to design and deploy a lightweight web-based interface.

C. Deployment Framework

To enable real-world applicability, the trained model was integrated into a web-based diagnostic platform developed using Flask. The deployment architecture was designed to be lightweight, responsive, and suitable for integration into clinical workflows. When a user uploads an MRI scan through the interface, the backend automatically performs preprocessing steps to standardize the image format and dimensions. The processed image is then forwarded to the VGG16 feature extractor, where spatial representations are generated. These extracted features are subsequently passed to the XGBoost classifier, which produces the final prediction

D. Evaluation Strategy

The effectiveness of the stroke classification framework was assessed using widely accepted performance metrics for medical diagnostic systems. Accuracy was used to measure overall prediction correctness, while precision evaluated the reliability of positive stroke predictions. Recall, also referred to as sensitivity, measured the model's ability to correctly identify actual stroke cases, which is particularly important in medical screening applications. The F1-score was computed to provide a balanced representation of precision and recall, ensuring that neither false positives nor false negatives disproportionately influenced evaluation results.

To obtain statistically reliable performance estimates, a five-fold cross-validation procedure was implemented. In each fold, the dataset maintained a 70 percent training split, 15 percent validation split, and 15 percent testing split while preserving class balance through stratified sampling. This structured validation approach minimized sampling bias and provided a comprehensive assessment of the model's ability to generalize across unseen data.

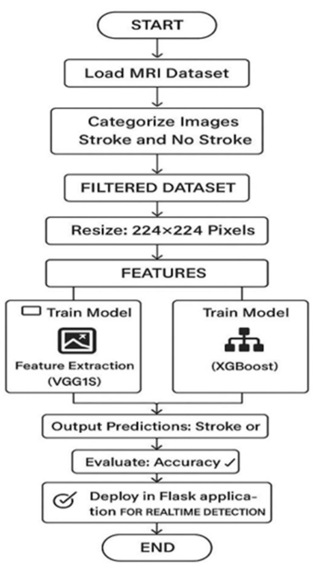


Fig .1 Overall Architecture

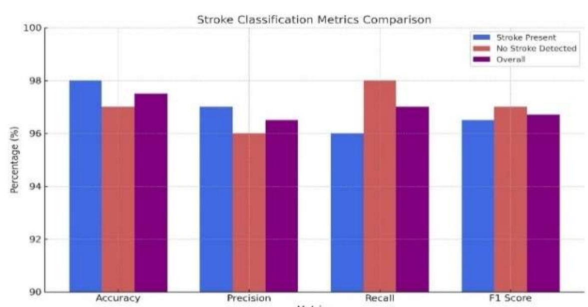


Fig 2. Results Graphical-representation

E. Overall Workflow

The complete system follows a structured pipeline beginning with MRI image acquisition and preprocessing, followed by augmentation to enhance dataset diversity. The standardized image is then processed through the VGG16 network for deep feature extraction. The resulting feature vectors are flattened and forwarded to the XGBoost classifier for binary classification. Grad-CAM visualization is subsequently applied to provide interpretability, and the final diagnostic output is delivered through the web interface. This hybrid and systematically designed architecture combines deep learning–based spatial understanding with efficient machine learning classification. As a result, the system achieves strong diagnostic performance while maintaining computational efficiency, interpretability, and real-time usability in clinical environments.

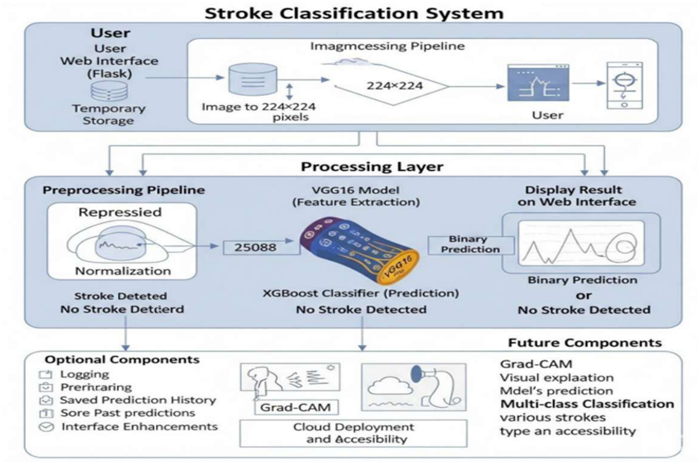
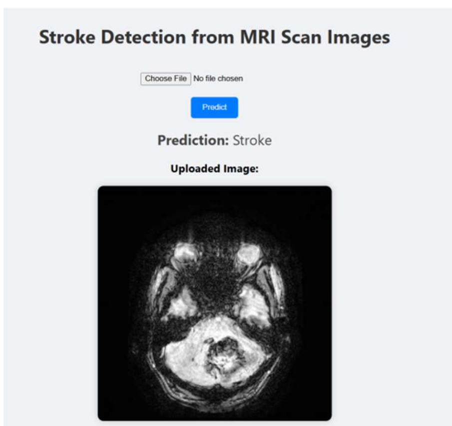


Fig 3 Stroke Classification Model Workflow

IV. Result

The image shows the MRI Scan which contain Stroke.



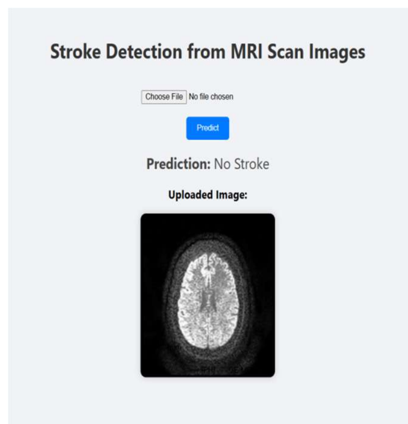


Fig 4: Results of Stroke MRI Scanned Image

Fig 5: Result of No Stroke MRI Scanned Image

V. Conclusion

Stroke Classification System shows that an AI-assisted hybrid system could yield effective stroke diagnosis from MRI images. Using VGG16 feature extraction with XGBoost classifier, it yields 97.5% accuracy that matches well with experts' decisions and is stable with changing imaging conditions. As a web program, it yields fast, interpretable, consistent results amenable to real-time use at the clinician's desktop. Further potential gains could be made by using multi-class stroke classification, interaction with larger, more diverse datasets from hospitals, and optimization for edge use on smartphones for use by patients at home or by first-response teams. Integration with HIS, PACS, or EMR programs could bring workflow automation by enhancing its use. Explainable dashboards and longitudinal follow-up capabilities could realize its greater clinical potential. The system is an extensible solution that enables AI-assisted stroke diagnostics by reducing delays and improving patients' outcomes.

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