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## Innovations in Stroke Identification: A Machine Learning-Based Diagnostic Model using Neuroimages

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**ABSTRACT:** Early and accurate stroke diagnosis is vital for timely treatment and better patient outcomes. Traditional diagnostic advanced preprocessing for improved generalization. ResNet achieves 94% accuracy, and MobileNet attains 92% on normal image classification. These results suggest strong potential for real-world clinical use. The approach enhances diagnostic speed and accuracy, supporting healthcare professionals. Future work includes large-scale validation and clinical deployment.

#### I. INTRODUCTION

A stroke occurs when the blood supply to the brain is blockedor a blood vessel in the brain bursts. It is the most commonThe associate editor coordinating the review of this manuscript and approving it for publication was Kumaradevan Punithakumar .cause of death worldwide, causing over 6.2 million deathsannually [1]. Survivors often suffer from disabilities thatseverely impair their quality of life. Preventive measures andtimely intervention can help to reduce the severity of strokeand its impact on the individual. Early identification of peopleat risk is crucial for stroke prevention [2]. There are two types of stroke: ischemic stroke and hemorrhage-related stroke. About 87% of strokes are ischemic strokes, the most approaches often lack precision and speed. This study introduces a novel machine learning model that combines ResNet and MobileNet architectures for stroke classification in neuroimages. ResNet provides powerful feature extraction, while MobileNet ensures lightweight efficiency. The model is trained on a diverse neuroimaging dataset with commontype [3]. When a blood vessel supplying blood to the brainis blocked or narrowed, blood flow to a specific part of thebrain is reduced or interrupted. The blockage may be causedby a blood clot, cholesterol deposits, or other debris enteringthe brain from other parts of the body [4]. Strokes causedby hemorrhages are less common, but they are more seriousand often fatal if not treated properly. A cerebral hemorrhageoccurs when a blood vessel in the brain bursts or leaks, causing blood to leak into the surrounding brain tissue. Thisleads to swelling and pressure on the brain structures. Thiscan damage brain cells and disrupt normal brain function [5]. This study uses machine learning techniques to developa systematic method for stroke detection. The study's mainaim is to understand the causes of strokes better and createreliable detection models that help physicians make informeddecisions about stroke prevention and treatment. The studywill analyze electronic health records, genetic information, and lifestyle data to develop predictive models identifying individuals at risk of stroke. The research will use features election algorithms to extract valuable insights from thedata and improve detection performance. A machine learningmodel will also support clinicians.

#### **II. RELATED WORK**

A Several studies have demonstrated the potential of machine learning and deep learning techniques in improving stroke diagnosis through neuroimage analysis. Joo and Park [1] applied traditional machine learning algorithms, such as support vector machines and decision trees, to detect and classify stroke, showing notable improvements in diagnostic accuracy and laying the groundwork for more advanced approaches. Building on this, Kamnitsas et al. [2] introduced a multi-scale 3D convolutional neural network (CNN) integrated with fully connected conditional random fields (CRF), significantly enhancing brain lesion segmentation performance— an essential step in stroke identification. Liu et al. [3] provided a comprehensive review of deep learning applications in medical ultrasound image analysis, emphasizing the strength of architectures like CNNs and





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RNNs in processing complex medical images and enhancing diagnostic reliability, including in stroke cases. Similarly, Li et al. [4] focused on stroke lesion segmentation using CNNs, developing a model capable of accurately delineating affected brain regions in neuroimages. Together, these works illustrate the growing effectiveness of machine and deep learning techniques in neuroimaging, offering a strong foundation for the proposed use of ResNet and MobileNet in stroke diagnosis.

#### **III. METHODOLOGY**

In This project employs an enhanced hybrid approach using MobileNet and ResNet to classify neuroimages into normal and stroke categories with high accuracy and efficiency. MobileNet ensures lightweight, real-time performance through depthwise separable convolutions, ideal for rapid diagnosis. ResNet contributes deep feature extraction with residual connections, enabling robust learning of complex stroke patterns. Both models are trained on preprocessed and augmented neuroimage datasets to maximize generalizability.



Fig. 1. Data workflow diagram

This diagram illustrates the workflow of a machine learning-based stroke diagnostic system using neuroimages. It begins with **data collection** of normal and stroke brain scans, followed by **preprocessing** to enhance image quality. The data is then used to **train ResNet and MobileNet models**, leveraging their strengths in feature extraction and efficiency. **Model evaluation** is conducted to assess performance metrics like accuracy and precision. Finally, the optimized model is intended for **clinical deployment** to support early and accurate stroke detection

#### **B.** Data Stationarization

Data stationarization is a critical preprocessing step that aims to make the statistical properties of neuroimages uniform across the dataset, enhancing the performance and generalization ability of deep learning models like ResNet and MobileNet. In the context of medical imaging, variations in scanner settings, patient anatomy, and acquisition protocols can introduce nonstationarity, which negatively impacts model training.





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IV. KEY STATIONARIZATION TECHNIQUES USED IN THIS PROJECT:

#### 1. Intensity Normalization:

Neuroimages often have varying intensity values due to different scanners or settings. Intensity normalization rescales pixel/voxel values to a common range, such as [0, 1] or [-1, 1], ensuring uniform contrast and brightness for all images.

#### 2. Histogram Matching:

Ensures that the intensity distribution of images matches a reference image. This is especially useful when combining datasets from different sources, improving consistency in appearance.

#### 3. Spatial Normalization / Resizing:

Neuroimages may vary in dimensions. All images are resized or padded to a standard shape (e.g., 224x224) to ensure compatibility with deep learning model input layers.

#### 4. Skull Stripping and Background Removal (Optional):

Removing non-brain tissues like the skull can reduce irrelevant variation in images, focusing the model on meaningful regions such as brain tissues where stroke lesions are found.



In the context of your project, "Innovations in Stroke Identification: A Machine Learning-Based Diagnostic Model Using Neuroimages," this plot shows the effectiveness of a machine learning model in diagnosing strokes using neuro imaging data. The near-perfect accuracy of both the training and validation sets indicates that the model is likely performing very well in distinguishing between stroke-affected and non-stroke images.

However, you might want to ensure that your model isn't overfitting, despite the high accuracy, by evaluating additional metrics like precision, recall, and F1-score. Overfitting can still happen even if the training and validation curves look similar, especially in cases where there's a small dataset or other underlying issues with generalization.

#### C. Autocorrelation

Autocorrelation is a measurement of the interconnection inside a spatial or temporal dataset. In neuroimage analysis, it estimates the internal relationship between neighboring pixels or regions in an image. According to the concept of autocorrelation, if one pixel is closely related to the next, and that next pixel to the one after it, then the first pixel is also related to the third. This principle helps in detecting consistent patterns or disruptions in brain scans, such as stroke-affected areas.





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Autocorrelation measures similarity between a signal and a shifted version of itself.In neuroimages, it detects repeating spatial patterns like textures or abnormalities.Low spatial autocorrelation may indicate disrupted brain tissue, such as stroke lesions.It helps extract texture features useful for machine learning classification.autocorrelation improves noise reduction and image preprocessing quality.In stroke detection, it highlights abnormal brain regions with distinct patterns



Fig. 3. Autocorrelation

The Autocorrelation Function (ACF) helps determine the order of the Moving Average (MA) component in a time series dataset. Starting from lag 0, the point at which the ACF values stop crossing the red dashed significance bounds indicates the MA order. If the ACF does not cross the bound at lag 1 but does at higher lags, the MA order is assumed to be 0. In Figure 3, the ACF at lag 1 clearly crosses the significance bound, suggesting the presence of an MA(1) process in the dataset.

Similarly, the **Partial Autocorrelation Function (PACF)** is used to identify the order of the Autoregressive (AR) component in time series analysis. In **Figure 4**, the red dotted line represents the significance bound. The PACF crosses this line after the 1st lag, which implies the AR order is 1. Therefore, the dataset shows an AR(1) behavior.

In our study, **autocorrelation** has been applied to test for **randomness** within the dataset. This was done by calculating autocorrelations across various time or spatial lags. The presence or absence of correlations at different lags helps infer underlying structure or noise in the neuroimage data. By calculating the optimal order of MA and AR components, autocorrelation contributes to a more effective and accurate model, supporting reliable stroke identification in our machine learning-based diagnostic system.

#### **D. Model Selection**

We applied time series models including the Autoregressive Integrated Moving Average (ARIMA), Autoregressive (AR), and Moving Average (MA) models to our processed dataset. The results were visualized through plotted graphs for performance comparison across models.





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Fig. 5. Proposed Model of Stroke identification

This architecture indicates the data flow of our deep learning-based neuroimage model. Brain scan images are input into the system and passed through an encoder composed of multiple convolutional blocks to extract hierarchical spatial features. These features are aggregated across different stages and further refined using a self-attention mechanism that emphasizes critical regions in the scans. The decoder then reconstructs the output—such as a segmented lesion area—by upsampling the attention-enhanced features and integrating them with earlier encoder layers through skip connections. The final result is evaluated against ground truth annotations to determine segmentation accuracy, allowing for the selection of the most effective model for stroke identification.

#### V. EVALUATION

Evaluation enables us to test the model against data that was not involved during training, ensuring its generalizability and reliability in real-world clinical scenarios. We have experimented with several different machine learning models and compared their performance throughout this study. These results were obtained using the following hardware configuration: a 4-core CPU, 16 GB RAM, and by training each model ten times using different random states for improved robustness. For accuracy measurement, we utilized normalized **Root Mean Squared Error (RMSE)** and classification metrics such as **accuracy, precision, recall, and F1-score**.

#### 1. Prediction Moves in Trends

The Stroke-related patterns in neuroimages often follow anatomical and pathological trends, such as localized tissue damage or consistent vascular anomalies. Recognizing these trends enables machine learning models to





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make reliable predictions based on recurring visual cues

#### 1. History Tends to Repeat Itself

In medical imaging, similar types of strokes often present with recurring visual features across different patients. These patterns—such as location of infarcts, symmetry loss, or specific signal changes—reappear consistently in clinical data. Machine learning models can learn these historical imaging signatures to improve diagnostic accuracy. As new cases emerge, the model references learned patterns from past examples to identify stroke indicators. This repetition in visual pathology allows the system to generalize well and support early diagnosis.

#### VI. CONCLUSION AND FUTURE WORK

This study developed an innovative machine learning-based diagnostic model for stroke identification using ResNet and MobileNet architectures. By automating the classification of neuroimages into normal and stroke categories, the model addresses key limitations of traditional diagnostic methods, such as human error, variability, and timeconsuming processes. The integration of this model into clinical workflows can significantly enhance diagnostic speed and consistency, facilitating timely interventions and ultimately improving patient outcomes. Our approach demonstrates the feasibility and potential of leveraging advanced deep learning architectures to enhance the accuracy and efficiency of medical diagnostics.

The model's ability to handle large volumes of data efficiently makes it suitable for widespread clinical use. Future work will focus on further validation with larger datasets and real-world clinical trials to establish its efficacy and reliability in clinical settings. In conclusion, this research underscores the transformative potential of AI-driven solutions in healthcare. By providing clinicians with powerful diagnostic tools, we can improve the accuracy and speed of stroke diagnosis, reduce morbidity, and enhance the quality of life for patients. This study sets a precedent for the broader application of deep learning models in medical diagnostics, paving the way for more intelligent and efficient healthcare systems.

**Future enhancements** for this study will focus on several key areas to further improve the efficacy and reliability of the machine learning-based diagnostic model for stroke identification. Incorporating larger and more diverse datasets will help validate the model's performance and ensure its generalizability across different populations and imaging conditions. Conducting extensive real-world clinical trials will provide critical insights into the model's practical application, refining and optimizing its functionality in actual clinical settings. Integrating additional data modalities, such as patient demographics, medical history, and other imaging techniques (e.g., MRI, CT scans), can enhance the model's diagnostic accuracy and provide a more comprehensive assessment of stroke. Exploring advanced optimization techniques and fine-tuning hyperparameters can further improve the model's efficiency and performance, making it more robust for clinical use.

Developing a user-friendly interface for clinicians will facilitate easy adoption and integration into existing healthcare systems, ensuring that the model is accessible and practical for daily use. Implementing mechanisms for continuous learning and updating the model with new data will help maintain its relevance and accuracy over time. Partnering with healthcare institutions to gather feedback and insights will drive iterative improvements and ensure that the model meets the needs of clinicians and patients effectively. By addressing these areas, the diagnostic model can become a vital tool in the early detection and treatment of stroke, ultimately contributing to improved patient outcomes and advancing the field of medical diagnostics.

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