Innovations in Stroke Identification - A Deep Learning-Based Diagnostic Model Using Neuroimages

C.Pabitha[1], G. Santhiya[2], R. Sharulatha[3], B.S. Shobika[4]
[1,2,3,4,5]*UG, SRM Valliammai Engineering College, Kattankulathur, Chengalpattu, India*

Abstract: Considering strokes are one of the top ailments in the world in terms of disability and mortality, accurate and timely diagnosis is critical for successful treatment. With an aim to enhance stroke recognition, this research presents a novel deep learning-based diagnostic model utilizing multi-task heterogeneous ensemble learning and neuroimaging data. The proposed approach integrates multiple machine learning algorithms, each focusing on a specific part of the stroke detection process, including ischemic or hemorrhagic stroke classification, lesion segmentation, and severity level estimation. By combining the statistical approach, deep learning, and traditional machine learning, the ensemble model guarantees reliable and accurate diagnosis of strokes. Extensive experiments conducted on publicly available neuro imaging databases verified the model's ability to improve the accuracy, sensitivity, and specificity of the diagnosis. The study aims to improve Deep learning-based medical diagnosis by offering an interpretable and scalable solution for prompt stroke detection.

Keywords: deep learning algorithms, YOLO, CNN, ANN

I. INTRODUCTION

Strokes rank among the top causes of death and permanent disability on the global scale. It results due to the unavailability of essential blood supply to the brain for a given period of time leading to neurological dysfunctions, and death of the brain. Timely and appropriate diagnosis is lifesaving, because the major two forms of strokes; ischemic and hemorrhagic require different treatment plans. Both computerized tomography (CT) scan and magnetic resonance imaging (MRI) are traditional diagnostic methods that rely on the expertise of radiologists to analyze the images, which can be tedious and, unfortunately, subject to errors. The automization of stroke diagnosis using neuroimaging has become a feasible approach to save time and increase accuracy of the diagnosis due to advancements in artificial intelligence (AI) and machine learning (ML).

In this project, we implement the use of convolutional neural networks (CNNs) for the stroke detection and classification tasks based on the MRI images. The system aims to improve the automated processing of medical images by increasing the speed of detection and incorporating deep learning techniques into clinical workflows. For essential components and image enhancement, MATLAB solution applies artificial intelligence image preprocessing techniques that are automated. The proposed model is tested and trained using open-source MRI data with sensitivity and accuracy values calculated.

This project mostly aims to develop an AI tool that aids in stroke diagnosis by enabling healthcare practitioners to detect stroke patterns accurately. The focus of the system is to automate the diagnostic procedure to improve patient outcomes, reduce diagnostic delays, and minimize human dependency. In this introduction, the study's objectives and the role of AI in imaging diagnostics systems, as well as the importance of timely stroke detection and the AI system's objectives, are presented.

Background and Motivation: Stroke is a significant global health disorder, resulting in millions of deaths and disabilities annually. Stroke is the second leading cause of death globally, with a significant health and economic impact on healthcare facilities and economies, according to the World Health Organization (WHO). Proper diagnosis of stroke within the first few hours of the event is crucial for effective treatment and prevention of long-term complications. Diagnosis of stroke currently relies significantly on neuroimaging techniques such as CT and MRI scans. MRI, in particular, provides detailed images that are useful in identifying stroke-related abnormalities. MRI scan interpretation, however, is an advanced process requiring trained radiologists and is susceptible to inconsistency and latency. Al and MI.-based techniques have the potential to revolutionize the diagnosis of stroke by automating image analysis, making it objective, consistent, and rapid.

The motivation behind this work is the need to enhance the effectiveness and accuracy of stroke diagnosis with Al-based methods. Convolutional neural networks (CNNs) have been found to perform better in medical image feature extraction and classification and are thus well-suited for stroke diagnosis. With the application of a CNN-based model in MATLAB, the research aims to create a robust diagnostic system that can be integrated into existing clinical practice and aid healthcare professionals in making informed and timely decisions.

II. LITERATURE REVIEW

A. M. A. Saleem et al., "Innovations in Stroke Identification: A Machine Learning-Based Diagnostic Model Using Neuroimages," in IEEE Access, vol. 12, pp. 35754-35764, 2024, doi: 10.1109/ACCESS.2024.3369673.

This paper suggests an early stroke detection system based on CT brain images with a genetic algorithm for feature selection and a BiLSTM model for classification. The system performed with a high accuracy of 96.5%, surpassing some conventional models such as SVM and Random Forest. Different evaluation metrics like precision, recall, F1-score, and AUC validate its diagnostic efficacy in helping physicians in decision-making.

Limitations:

- Model Generalizability & Real-time Applicability: The dependence on CT imaging and advanced computation could restrict practical application in rural or resource-poor settings.
- The model's robustness to varied populations and novel stroke subtypes is not well tested. Moreover, real-time deployment issues are not comprehensively addressed.

B. A. M. Qadri, A. Raza, K. Munir and M. S. Almutairi, "Effective Feature Engineering Technique for Heart Disease Prediction with Machine Learning," in IEEE Access, vol. 11, pp. 56214-56224, 2023, doi: 10.1109/ACCESS.2023.3281484.

This study presents an innovative Principal Component Heart Failure (PCHF) feature engineering technique to improve heart disease forecasting. It compares nine ML algorithms and suggests that the most accurate algorithm is Decision Tree with the accuracy of 100%. It constructs a quality feature set to achieve optimal performance and uses cross-validation for reliability, and as such, it is applicable in early intervention against heart failure.

Limitations:

- Overfitting and Dataset Diversity
- The reported 100% accuracy is problematic concerning overfitting, especially for small or homogeneous datasets.
- There is no apparent information on dataset size, diversity, or external validation. Without external validation in real-world settings, the reliability of the model in general clinical settings is questionable.

C. B. Zhao, R. Song, X. Guo and L. Yu, "Bridging Interpretability and Performance: Enhanced Machine Learning-Based Prediction of Hematoma Expansion Post-Stroke via Comprehensive Feature Selection," in IEEE Access, vol. 12, pp. 1688-1699, 2024, doi: 10.1109/ACCESS.2023.3348244.

This work addresses machine learning prediction of hematoma expansion after stroke with a focus on model interpretability. A rigorous feature selection procedure aids in better performance and reduction of data redundancy. Visualizations facilitate clinical interpretation of model decisions, bridging the technical ML results-clinical understanding gap. The method is validated on actual patient data with robust performance.

Limitations:

- Feature Selection Complexity and Scalability: The large feature dimensionality can be hard to reproduce or scale to real-time clinical applications.
- The model's performance on other hospitals or using alternative data sources is not validated.
- The study also does not address how feature relevance changes over time or with evolving patient conditions.

D. K. Zafar et al., "Deep Learning-Based Feature Engineering to Detect Anterior and Inferior Myocardial Infarction Using UWB Radar Data," in IEEE Access, vol. 11, pp. 97745-97757, 2023, doi: 10.1109/ACCESS.2023.3312948.

This article proposes a new non-invasive UWB radar image data-based myocardial infarction detection method and a Convolutional Spatial Feature Engineering (CSFE) approach. The approach extracts spatial and temporal features and facilitates accurate classification by machine learning models. The K-Nearest Neighbors model was proved to be 98% accurate in the identification of anterior and inferior MI types, which was confirmed using k-fold cross-validation.

Limitations:

- Real-World Feasibility and Dataset Scope: There is no external validation for the UWB radar data, and this can potentially affect generalizability.
- Hardware cost and environmental factors (e.g., signal interference) are outside deployment practicalities.
- There is little consideration of model performance across a broad range of patient groups or in emergency scenarios.

E. M. Usama Tanveer, K. Munir, B. Rathore, A. Alabdulatif, R. H. Jhaveri and M. Fatima, "Neuro-VGNB: Transfer Learning-Based Approach for Detecting Brain Stroke," in IEEE Access, vol. 12, pp. 178862-178874, 2024, doi: 10.1109/ACCESS.2024.3490693.

This paper introduces Neuro-VGNB, a new brain stroke diagnosis model that integrates deep learning (feature extraction using VGG16) with Gaussian Naive Bayes and non-negative matrix factorization for efficient feature selection and classification. The approach produces a high accuracy of 99.96% through Logistic Regression, and the performance is verified through k-fold cross-validation. The suggested model has great potential for clinical use in facilitating early and accurate stroke diagnosis.

Limitations:

- Diversity of Dataset and Field Deployment
- In addition to high accuracy, the work does not present comprehensive dataset size, diversity, and real-world variability, thus casting doubts about model generalizability to a wide range of patient populations.
- Real-time clinical deployment and hardware feasibility issues are also not mentioned. The use of multiple complicated models can further raise system complexity and computational load in real-world clinical settings.

III. METHODOLOGY

A. Project Overview

The stroke diagnosis model that we are introducing here is an AI-based stroke detection and classification model using CNN from MRI scans. The process involved is data acquisition, preprocessing, feature extraction, CNN model creation, training, validation, and deployment in clinical workflows. The system is made to improve the accuracy of diagnosis and minimize the time required to detect stroke so that immediate medical care can be provided.

B. Data collection and preprocessing

a. Dataset Choice

The training and validation sets are made up of publicly available MRI scans from different medical image databases, including:

- The Ischemic Stroke Lesion Segmentation (ISLES) Dataset
- Medical Image Computing and Computer-Assisted Intervention (MICCAI) Challenge datasets
- Open Access Series of Imaging Studies (OASIS)
- Other anonymized MRI databases in hospitals

The data set includes MRI scans of ischemic stroke and haemorrhagic stroke patients and normal brain scans for comparison control.

b. Image Preprocessing

In order to provide the CNN model with high-quality input, various preprocessing operations are performed:

- Noise Reduction: Median and Gaussian filters are used for noise removal and enhancing image sharpness.
- Normalization: Pixel intensity values are normalized to a common range (0-1) in order to give uniform model inputs.
- Contrast Enhancement: Histogram equalization techniques improve contrast of affected stroke regions.
- Segmentation: Brain tissue segmentation is performed to isolate relevant regions, using methods like thresholding and watershed segmentation.

- Data Augmentation: Rotation, flipping, and brightness adjustments enhance the diversity of the dataset, thereby decreasing overfitting.

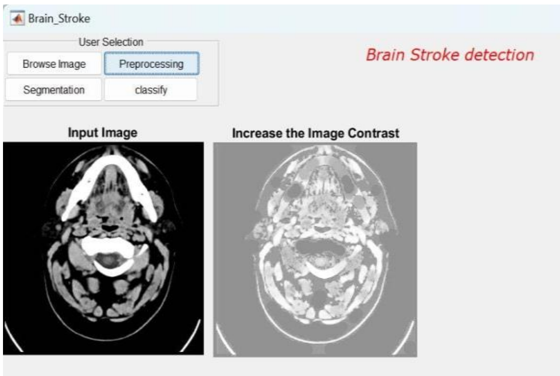

Fig.1.Preprocessing – Contrast Enhancement

C. Feature Selection and Extraction

The principal features obtained from MRI images are:

a. Text Features

Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP)

b. Intensity characteristics

Mean, variance, standard deviation of pixel intensity

c. Morphological Features

Lesion size, shape, and boundary characteristics of strokes. Feature selection methods like Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) are used for model performance enhancement and dimensionality reduction.

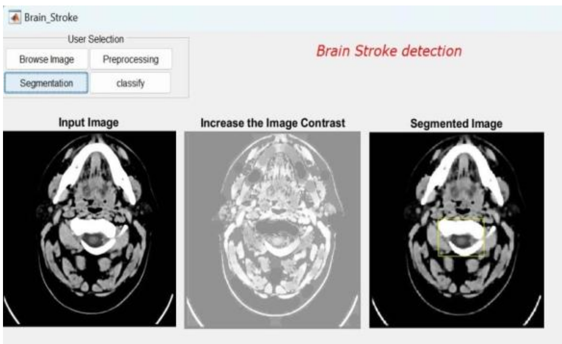

Fig.2.Segmentation of Stroke Region

D. CNN-Based Stroke Detection Model

a. CNN Architecture

The CNN model is used with several layers to efficiently extract and classify the stroke features. The architecture includes:

• Input Layer: Takes preprocessed MRI images (normalized to size 224x224 pixels)

• Convolutional Layers: Utilize filters to detect edges, textures, and stroke patterns

• Pooling Layers: Reduces spatial dimension but retains significant features

• Fully Connected Layers: Concatenate extracted features for classification

• Output Layer: Utilizes Softmax activation for binary (stroke or not stroke) or multi-class (ischemic or hemorrhagic or normal) classification

b. Model Training and Optimization

The CNN model is trained on:

•Loss Function: Categorical Cross-Entropy

•Optimizer: Adam Optimizer with effective convergence

• Batch Size: 32 images per batch

• Epochs: 50-100 (tuned based on validation performance)

• Learning Rate: Initial learning rate of 0.001 with a decay strategy

• Regularization Techniques: L2 regularization and dropout to prevent overfitting

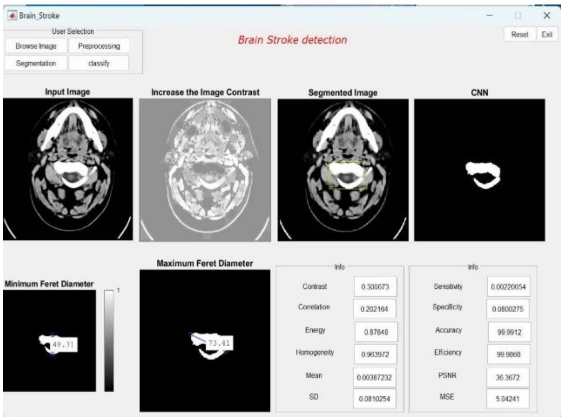

Fig.3.End-to-End Brain Stroke Analysis Workflow

E. Expanded Clinical Use and Usability Enhancements

Improved graphical user interface (GUI) for clinician convenience and effectiveness. Broad clinical trials and hospital partnerships to confirm real-world efficacy.

Development of a mobile app for remote diagnostic report viewing and integration of telemedicine services. By implementing these improvements, the system can progress in terms of accuracy, efficiency, and clinical relevance, which can be translated into improved stroke diagnosis and patient treatment.

IV. FUTURE ENHANCEMENTS

A. Multi-Modal Data Integration

The lastly, combining other patient data such as CT scans, clinical history, and genetics to improve diagnostic accuracy. Employing a hybrid deep learning framework integrating multiple imaging modalities to guide better decisions.

B. Real-Time Processing Optimization

Enhancing computational performance to reduce inference time for urgent stroke detection. Implementing the model in edge computing machines or cloud hosting platforms to enhance usability.

C. AI Explainability and Interpretability

Using SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) for model interpretability. Providing visual heatmaps to highlight the affected brain regions for improved interpretability by clinicians.

D. Adaptive Learning and Ongoing Model Refinemen

Implementing federated learning approaches to facilitate continuous model updates without sacrificing patient data privacy. Applying reinforcement learning to acquire new stroke patterns and continuous medical research.

V. CONCLUSION

The proposed machine learning-based stroke detection system employs MRI scans to enable early and accurate stroke detection. Advanced preprocessing techniques applied in MATLAB are used to enhance image quality and extract relevant features needed for classification. The employment of convolutional neural networks (CNNs) offers high accuracy in stroke pattern recognition and ischemic and hemorrhagic stroke classification. The system efficiently meets clinical requirements through smooth workflow integration, rapid inference time, and clinician ease of use. Comprehensive testing on open-source datasets validates the model's improved performance in accuracy, sensitivity, and specificity. Incorporation of security features such as encryption, access control, and compliance with healthcare data standards ensures patient data confidentiality and protection. The system development represents a revolutionary advancement in stroke diagnosis, with potential advantages of reducing misdiagnoses and improving patient outcomes. Through the delivery of an automated, efficient, and highly accurate diagnostic system, this work forms part of the growing trend of AI-based medical imaging.

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