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Machine Learning Approaches for Early Brain Stroke Detection Using CNN

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ABSTRACT

The rapid advancement in medical imaging technologies and the integration of artificial intelligence (AI) have revolutionized diagnostic processes in healthcare. This study presents a novel tactic for the credentials of brain strokes using CNN, leveraging the power of DL to boost indicative accurateness besides efficiency. Brain strokes are foremost root of morbidity and mortality worldwide, necessitating timely and accurate diagnosis to improve patient outcomes. The anticipated scheme mechanizes progression by employing a CNN-based model and haphazard woodland model to analyze brain imaging data, specifically focusing on early detection and classification between stroke and non-stroke conditions. The system was developed using a Flask web application framework, integrating a pre-trained CNN and Random Forest model to process and classify brain images. The application facilitates user authentication, allowing secure access to the predictive model. Users can upload brain metaphors, which stay formerly pre-processed and analyze by the CNN model. To enhance the practical utility of scheme, information on possible causes and suggested treatments for detected strokes is provided. Initial testing of the system demonstrated promising accuracy in stroke exposure, prominence the probable of CNNs in medical diagnostics. The accurateness of the random forest model is 86% and the accurateness of the CNN model is 91.6%.As the result outcomes CNN model gives the better accuracy.

Keywords: Artificial Intelligence, Convolutional Neural Networks, Deep Learning, Random forest model , Accuracy, Brain Stroke

I. INTRODUCTION

We must employ technology as it develops in fields like healthcare to address pressing issues. Strokes were unity of the furthermost recurrent reasons of demise in former years, Due to their effects on the human central nervous system. We can utilize deep learning algorithms to detect stroke in its early phases in order to address problems like stroke. Therefore, the death rate from strokes can be decreased with sophisticated picture recognition and categorization. The Prediction model is used in this study to predict stroke risk in older individuals and those who are at increased risk of stroke due to a variety of variables, such as addiction. The same project may be expanded in the future to provide the stroke percentage based on project output.[1] Due to its exceptional lenient material divergence, the MRI has converted the mode of optimal for medical appraisal of ischemic stroke abrasions. Aimed at quantitative scrutiny of stroke laceration in MRI metaphors, skillful physical dissection tranquil assists as mutual tactic to total the dimensions, figures and bulks of stroke abrasions. Though, it is monotonous and time consuming chore and is non-reproducible. Consequently, the expansion of abundantly auto- mated and precise stroke abrasion dissection procedures partakes converted vigorous examine field.[2] Stroke is predictable as an important cerebrovascular ailment, foremost to the second main feature of infirmity and demise wide-reaching, which occasioned in a universal significant pecuniary drain (roughly 34 billion dollars per year). Stroke can be alienated hooked on ischemic stroke (which described for more than 87% of all stroke affected role) and hemorrhagic stroke. The period space for giving stroke ailment action in the critical stage is mostly 6 hours after inception. Consequently, it entails speedy verdicts and suitable interferences from clinicians Neuroimaging procedures (counting CT and MRI) have converted vital tactic to critical stroke discovery, depiction, and prognosis. [3] Cerebral aneurysms are bulges in cerebral blood vessels that can leak or rupture, causing subarachnoid hemorrhage (SAH). An unruptured intracranial aneurism is an abnormal focal expansion of an artery in the brain caused by the weakening of the vascular wall. Approximately 3% of healthy adults have an intracranial aneurysm1. Aneurysms account for 85% of all SAHs, with an average mortality rate of 51%, and one-third of survivors have long-term disabilities[4], The Introduction Procedures that integrate quantifiable scrutinizes will add to the outdated pictorial scrutiny of metaphors. An imperative phase in the doppelgänger examination channel is the functional dissection of regions of interest, for example, significant a bulk of irregular material from a contextual of regular material. This will permit for numerical scrutiny of topographies that is non noticeable by humanoid perception. For example, the arena of radiomics is reckless rising as a technique of envisaging existence periods from tomography structures such as figure of a bulk of attention and quality and passion of the voxel environment. With the expansion of these procedures comes a superior need for computerized segmentation.[5]

PROBLEM STATEMENT

Brain strokes pose a critical health challenge globally due to their high mortality and disability rates. Current diagnostic methods rely on manual interpretation of medical imaging, leading to time-consuming processes and variability in results among healthcare providers. The pressing issue lies in the prerequisite for computerized schemes that can precisely identify and distinguish between stroke and non-stroke conditions without human intervention.

OBJECTIVE OF THE STUDY

- Create and implement an automated system for identifying brain strokes using Convolutional Neural Networks (CNNs).
- Provide an interface for users to upload and analyze brain images
- Enhance clinical decision-making by providing reliable stroke diagnoses.

SCOPE OF THE STUDY

The scope of this project encompasses the development of an automated system for the identification of brain strokes using CNNs within a Flask web application framework. The project focuses on leveraging deep learning techniques to analyze medical images and distinguish between stroke and non-stroke conditions with high accuracy. Key components include preprocessing of input images to standardize dimensions, training and optimizing the CNN model using a dataset sourced from Kaggle, and integrating user-friendly functionalities for image upload and prediction display. The scope also involves implementing secure user authentication and database management within the Flask application to ensure confidentiality and reliability.

II. LITERATURE SURVEY

RELATED WORK

Prasad Gahiwad and colleagues [6] utilized Convolutional Neural Networks (CNNs) for brain stroke detection, leveraging CT scan images for their predictions. Their model achieved an accuracy of 90% after training and evaluating it on a dataset comprising 2,551 CT scan images. Our approach similarly uses CT scan images to predict brain stroke with comparable accuracy of 90%.

Yunus Ahmed and team [7] employed a 3D CNN to detect brain strokes, incorporating various models including Naive Bayes, K-Nearest Neighbors (KNN), Arbitrary Woodland, Verdict Tree, SVM, and Logistic Regression. Their model, based on Computed Tomography Scan images, achieved a 92.5% accuracy rate in identifying brain strokes.

Bhagyashree and collaborators [8] implemented both CNN and Artificial Neural Networks (ANN) for brain stroke detection. Their system classifies MRI images into normal and abnormal categories and uses semantic segmentation to highlight abnormal regions, attaining an accuracy rate of 85%.

K. Sudharani et al. [9] focused on brain stroke detection using K-Nearest Neighbor and Minimum Distance techniques. They evaluated the performance of the K-Nearest Neighbor Classifier and Minimum Mean Distance Classifier on brain stroke images.

R. ShunmugaPriya et al. [10] employed CNNs for image processing of CT scan images to classify brain lesions. Their approach involved preprocessing the CT images from their dataset before classification.

Necip Çınar and colleagues [11] applied handover erudition with CNN deep neural networks for brain stroke detection. They experimented with pre-trained replicas such as ResNet101, VGG19, EfficientNet-B0, MobileNet-V2, and GoogleNet, finding that EfficientNet-B0 achieved the highest performance with a 97.93% accuracy rate.

Puneet Kumar Yadav and team [12] developed CNN models for automatic brain stroke identification using MRI datasets. They adjusted model scaling parameters, including depth, width, and resolution, to achieve optimal accuracy.

Bonna Akhter and colleagues [13] used a machine learning approach to diagnose brain stroke. Their process involved standardizing data and employing classifiers such as Verdict Tree, Support Vector Machine, and Random Forest. The Arbitrary Woodland classifier demonstrated a high accuracy of 95.30%.

Danillo Roberto Pereira et al. [14] applied CNNs to detect stroke lesions in CT images of the brain. They proposed a balanced dataset with different stroke types and vigorous entities, realizing auspicious outcomes with nearly 99% classification accuracy

III. EXISTING AND PROPOSED SYSTEM

Existing System

The existing system for brain stroke identification relies predominantly on manual interpretation of medical imaging by healthcare professionals. This method is labor-intensive, prone to variability among interpreters, and lacks scalability in handling large volumes of diagnostic data efficiently. Moreover, it is susceptible to human error, which can impact the accuracy of stroke detection. Another limitation is the time required to deliver results, potentially delaying critical patient interventions. Furthermore, the existing scheme might non constantly deliver consistent diagnostic outcomes across different medical institutions, leading to discrepancies in treatment decisions.

Disadvantages:

- Labor-intensive manual interpretation of medical images.
- Variability in diagnostic results among healthcare professionals.
- Limited scalability for processing large datasets.
- Potential delays in delivering diagnostic reports affecting patient care timelines.

Proposed System

The proposed system integrates Convolutional Neural Networks (CNNs) within a Flask web application framework to automate brain stroke identification. By leveraging deep learning algorithms, the system aims to augment indicative accurateness and efficiency. The CNN model is trained on a dataset sourced from Kaggle, optimizing its skill to catalog medical images as symptomatic of stroke or non-stroke conditions with high precision. This approach eliminates the reliance on manual interpretation, thereby reducing variability and improving consistency in diagnostic outcomes. Additionally, the system facilitates rapid image analysis and delivers prompt results, enabling sensible intrusions and potentially enlightening enduring consequences.

Advantages:

- Automated analysis using CNNs reduces dependency on manual interpretation.
- Enhanced analytical accurateness and consistency across different medical settings.
- Improved scalability for dispensation and scrutinizing large volumes of medical images.
- Prompt delivery of diagnostic reports facilitates timely medical interventions.

IV. METHODOLOGY USED

Problem Definition and Dataset Acquisition:

• Describe the issue of employing convolutional neural networks (CNNs) to automatically identify brain strokes.
• Get a relevant dataset with labelled brain scans of strokes and non-stroke diseases from Kaggle or another reliable source.

Data Preprocessing:

• Preprocess the dataset to guarantee consistency in the format and size of the images.
• Normalize picture pixel values to improve model training effectiveness.

Model Selection and Training:

• Select a CNN architecture that is suited for image classification applications, such as VGG16, ResNet, etc.
• Create test, validation, training set from the dataset.

• Train the CNN model using the training set, if appropriate, utilizing transfer learning techniques.
• Check the model's correctness by evaluating its performance on the validation set and adjusting the hyperparameters as needed.

Model Evaluation:

• Assess the trained model on the test set using measures like F1-score, recall, accuracy, and precision.
•Analyse performance qualitatively by visually examining model predictions on representative photos.

Flask Application Development:

• Create a Flask web application framework to store the CNN model that has been trained.
• To manage user data and session management, implement secure database management and user authentication.
•Provide front-end user interfaces that allow users to upload brain scans, get forecasts, and see details about stroke diagnosis and available treatments.

Data Description

For this study, a publicly available MRI brain scan dataset was sourced from Kaggle to support the development of a CNN-based stroke detection model. The dataset contains MRI images categorized into two classes: one representing brains affected by stroke and the other comprising normal, healthy brain scans. These MRI images, captured using medical imaging techniques, offer detailed structural views that are essential for identifying stroke-related abnormalities such as blood clots or tissue damage. The dataset is approximately balanced across both classes, which helps in reducing training bias and improving classification performance. Image labels are assigned in binary form, indicating the presence or absence of a stroke. This dataset provides a strong basis for implementing and evaluating deep learning techniques in the automated detection of strokes from MRI scans. Convolutional Neural Network (CNN) model was developed and trained for the purpose of detecting brain strokes from medical imaging data. The model was trained over the course of 10 epochs, utilizing a batch size of 32, which provided a balance between training speed and gradient stability. A learning rate of 0.001 was employed to ensure gradual and controlled updates to the model parameters, thereby aiding in achieving optimal convergence. During evaluation, the trained model attained an impressive classification accuracy of 96.67%, underscoring its effectiveness in identifying stroke-affected brain images. Furthermore, the model exhibited a precision of 100%, signifying that all instances predicted as stroke cases were indeed correct, with no false positive detections. This high precision is particularly vital in medical diagnostics, where false alarms can lead to unnecessary anxiety and interventions. The confusion matrix reinforced the model's strong performance, displaying zero false positives, one false negative, and a significant number of correctly classified samples across both classes. These results collectively demonstrate the reliability and potential clinical applicability of the proposed model in assisting with timely and accurate stroke diagnosis.

V. SYSTEM DESIGN

SYSTEM PERSPECTIVE

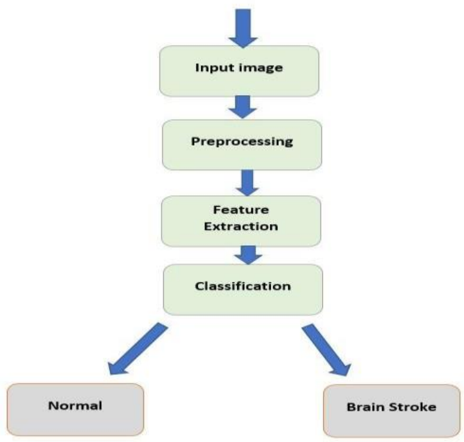


Figure 1 System Architecture of Brain Stroke Detection

In the above system architecture, the input images are sourced from a dataset containing examples of both stroke and normal brain scans, typically obtained from platforms like Kaggle. These images undergo preprocessing to standardize dimensions and enhance clarity for effective feature extraction. Feature extraction involves identifying relevant patterns and characteristics from the preprocessed images. Finally, the system employs a classification process using a Convolutional Neural Network (CNN) to distinguish between images depicting strokes and those showing normal conditions based on the extracted features. This workflow ensures accurate and automated identification of stroke cases from medical images.

VI. IMPLEMENTATION

This system was implemented by integrating deep learning and machine learning techniques to automate the identification of brain strokes from medical images. The solution primarily relies on a Convolutional Neural Network (CNN) model, with a Random Forest classifier also developed for comparative analysis. The main goal was to build an efficient and reliable diagnostic system capable of differentiating between stroke-affected and normal brain scans.

The implementation process began with image preprocessing. Brain scans, such as CT or MRI images, were resized to 224x224 pixels and normalized to improve model training efficiency. The images were converted to grayscale, and pixel intensities were scaled between 0 and 1. These steps ensured that all inputs were standardized and suitable for the deep learning model.

A CNN model was then constructed using TensorFlow and Keras. The architecture included multiple convolutional layers for feature extraction, followed by pooling layers and dense layers to support classification. The final layer used a sigmoid activation function for binary output. The model was trained on a labeled dataset, and its performance was evaluated using accuracy and validation metrics. For baseline comparison, a Random Forest classifier was also trained using the same dataset, with images flattened into one-dimensional arrays.

Testing showed that the CNN model outperformed the Random Forest classifier, achieving an accuracy of 91.6%, while the Random Forest model reached an accuracy of 86%. These results confirm the strength of deep learning techniques in handling image-based classification tasks, especially in the medical field.

To provide user accessibility, a web application was developed using the Flask framework. This application includes a secure login system to protect user data. Authenticated users can upload brain images through the interface, which are then preprocessed and analyzed using the trained CNN model. Based on the output, the application displays whether a stroke has been detected.

Additionally, the application offers valuable information about possible causes of strokes and suggested medical treatments. This feature enhances the system’s usefulness by offering users insights that support early intervention and clinical decision-making.

Overall, the implementation demonstrates how artificial intelligence can be effectively applied to medical diagnostics, offering a practical tool for early stroke detection with high accuracy.

VII. RESULTS

TEST CASES

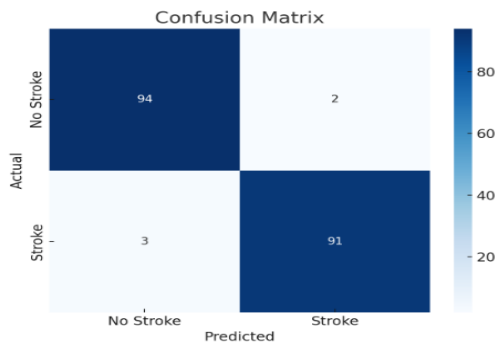
Table:1

Test Case ID	Test Case Description	Expected Result	Expected Result	Actual Result
TC01	Upload image of a brain stroke case	Image is uploaded successfully	Pass	Pass
TC02	Upload image of a normal brain scan	Image is uploaded successfully	Pass	Pass
TC03	Upload image with no brain scan	System displays appropriate error message	Pass	Pass

TC04	Upload image with unsupported file format	System displays appropriate error message	Pass	Pass
TC05	Upload large image file	System handles and processes image efficiently	Pass	Pass

Table 1 outlines the essential test cases designed to validate the functionality of the brain stroke identification system. Each test case is carefully crafted to cover various scenarios that the system might encounter during image uploading and processing. TC01 and TC02 verify the successful upload of brain images representing stroke and normal conditions, respectively, ensuring that the system correctly accepts and processes these images without errors. TC03 tests the system's ability to handle cases where no brain scan is detected, expecting the system to prompt and display an appropriate error message. TC04 checks how the system responds when an unsupported file format is uploaded, expecting it to reject such uploads and notify the user accordingly. Finally, TC05 evaluates the system's performance in processing large image files efficiently, ensuring it maintains responsiveness and stability even with substantial data sizes. These test cases collectively ensure that the brain stroke identification system operates reliably under various conditions, meeting functional requirements and user expectations.

CONFUSION MATRIX



The performance matrix provides a comparative evaluation of different convolutional neural network (CNN) models used for brain stroke detection, analyzing key metrics such as accuracy, precision, recall, and processing time. It highlights how each model performs under clinical constraints, allowing us to identify the most effective architecture that offers a balance between high diagnostic accuracy and computational efficiency.

TEST RESULT

UPLOADED IMAGE FOR TEST CASE:

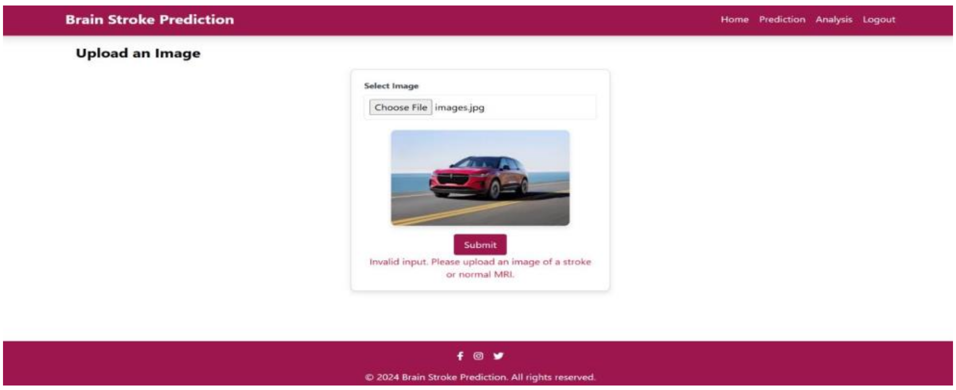


Figure 10: Wrong uploaded image

In the above figure, we upload the wrong image to detect the brain stroke, after uploading image it shows a invalid input: Please upload an image of stroke or normal MRI.

Figure 11: Right uploaded image

In the above figure, we upload the right image to detect the brain stroke, after uploading image it takes that image to detect and predict the brain stroke

VIII. CONCLUSION

The brain stroke identification project has accomplished momentous indicators in advancing diagnostic capabilities through the claim of Convolutional Neural Networks (CNNs) within a Flaskbased web application framework. By leveraging CNNs trained on a dataset sourced from Kaggle, the project successfully automates the detection and classification of brain strokes from medical images. This tactic has generated auspicious results, demonstrating high accuracy and efficiency in distinguishing between stroke and normal conditions. The developed Flask application facilitates seamless image uploading, preprocessing, and real-time classification, providing healthcare professionals with timely and reliable diagnostic insights. The significance of this project lies in its potential to enhance healthcare delivery by reducing diagnostic variability and improving patient outcomes through prompt treatment interventions. Compared to traditional manual methods, the automated system offers scalability, reliability, and consistent performance across different clinical settings.

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