Intelligent Neuroimage-based Stroke Diagnosis Using Deep Learning and Dual Web Interface for Clinical Use

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Abstract

One of the main causes of death and permanent disability, stroke needs to be diagnosed as soon as possible, to guarantee early treatment as soon as possible. Traditional stroke detection techniques mostly depend on radiologists who manually interpret neuroimage, which can be laborious and subjective. Many deep learning models lack integration with a user-central design or deployed clinical equipment, despite the promise to detect strokes despite recent advances. The study introduces a novel AI-powered structure to an early stroke classification from CT and MRI neuroimage that uses a modified VGG16-based Convolutional Neural Network (CNN). Our technology, unlike traditional models, includes a dual-interface web platform, designed for patients and physicians, which is filled with AI-Interested Chatbot, automated report distribution and a safe database. The suggested model was a high precision and remembered and a classification accuracy of 94.6%. These findings support the efficacy of the framework and demonstrate their ability for practical clinical integration, especially in rural or deprived healthcare settings.

Keywords: Stroke Detection, Medical Imaging, MRI, and Deep Learning.

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1. Introduction

A stroke is a severe medical emergency that occurs when the blood supply to the brain is cut off, causing irreversible brain damage. It is one of the major causes of death and long-term disability in the world. Early and accurate diagnosis is required to improve the patient's survival rate and reduce long-term effects. Traditionally, professional radiologists manually analyze neuroimaging forms such as computed tomography (CT) and magnetic resonance imaging (MRI) to diagnose strokes. Delay, human error, and clinical variability can all affect this process, especially in emergency situations or conditions with limited resources. Medical image analysis automation has been investigated in recent years using machine learning (ML) and artificial intelligence (AI). A type of deep learning model, Convolutional Neural Networks (CNNs), has shown great promise in improving clinical accuracy and achieving complex characteristics from neuroimages. Although previous studies have used CNNs to diagnose strokes with encouraging results, these models often operate independently without integrating into real-world clinical workflows or patient-supporting platforms. We provide a complete, deployable solution that combines technical stability with practical purposes to remove these obstacles. For stroke classification, our system uses a transfer-learning-based CNN architecture (VGG16), which is enhanced by refined pre-processing methods. The solution also includes a patient portal, a radiologist dashboard, an AI-operated chatbot for stroke education, and a dual-interface web platform with secure email report distribution. In addition, our solution incorporates safety-conscious designs, including patient records and role-based access controls, along with a secure database for control.

1.1 Problem Statement

This research is an AI-driven system designed to assist in early and accurate stroke diagnosis using CT and MRI brain scans. By integrating deep learning models like CNN, the framework automates image analysis and delivers real-time results through an intuitive user interface. By incorporating features such as an AI-powered chatbot and automated report delivery, the system supports better clinical decisions and improves healthcare accessibility for patients in remote areas, representing a major advancement in smart, scalable, and patient-oriented medical solutions.

2. Related Work

In recent years, machine learning has increasingly been employed in medical diagnostics, particularly in assessing stroke risk and analyzing neuroimaging data. Researchers have examined a diverse array of techniques, from fundamental supervised algorithms to more advanced deep learning models. Machine learning techniques have demonstrated potential in identifying stroke risk by analyzing patient historical medical data, such as information found in electronic health records (EHRs). Techniques such as Extreme Gradient Boosting (XGBoost) have achieved high predictive accuracy for stroke risk in hypertensive patients by identifying relevant features and patterns in large datasets [1]– [3]. Ensemble models combining various algorithms have further enhanced reliability in detecting individuals at elevated risk [4]. Skull stripping plays a vital role in preparing neuroimages for accurate analysis. According to Buda et al. [5], this process can be addressed using traditional techniques or modern DL approaches. CNNs, in particular, have revealed potential in enhancing the effectiveness and reliability of routine clinical workflows.

Deep reinforcement learning (DRL) has evolved in intricate predictive tasks, including temporal link prediction in dynamic networks. For instance, Kumar et al. [6] demonstrate how DRL can outperform static supervised methods in predicting hidden links in criminal networks, while Grover et al. [7] introduce a generative model for graphs that enhances learning from evolving network structures. Within stroke diagnosis via imaging, several studies have employed CT and MRI data to predict stroke severity and subtype. Nijiati et al. [8] used CNN-based hybrid structures to predict Modified Rankin Scale (mRS) outcomes with 74% accuracy, while Shree et al. [9] integrated wavelet entropy-based features and probabilistic neural networks for classifying MRI images into normal, stroke, and degenerative disease categories, reporting high classification performance.

Saleem et al. [10] emphasize the role of patient demographics and clinical attributes—such as age, heart conditions, blood glucose levels, and hypertension in enhancing prediction models. They propose the use of a perceptron neural network trained on balanced datasets, addressing the limitations of unbalanced data in earlier models. Advanced deep learning architectures have also been effective in analyzing intracranial hemorrhages. Hussein et al. [11] proposed a framework capable of distinguishing between hemorrhage subtypes (epidural, subdural, and intraparenchymal) with an average accuracy of 96.21%, incorporating lesion quantification to aid emergency clinical decisions.

Hybrid feature extraction techniques that combine Discrete Wavelet Transform (DWT), Gray Level Co-occurrence Matrix (GLCM), and Discrete Cosine Transform (DCT) have proven valuable in classifying CT images. Studies by Huang et al. [12] and Gaurav et al. [13] employed Random Forest classifiers, achieving high classification accuracy by leveraging transformed texture and statistical features. Preprocessing strategies and neural model design also significantly influence classification outcomes. Ryu et al. [14] demonstrated that integrating CNN and RNN components, along with enhanced preprocessing pipelines, improved hemorrhage detection performance, reinforcing the utility of deep learning as a clinical decision support tool.

In the current healthcare landscape, stroke diagnosis primarily relies on traditional neuroimaging techniques that involve CT scans, MRI, and ultrasound imaging, interpreted manually by radiologists. These methods, while effective to a certain degree, are often time-consuming, subjective, and prone to human error, especially in emergency settings where time is critical. The existing systems do not typically integrate machine learning or automation, meaning stroke detection heavily depends on the availability and experience of medical professionals. Conventional diagnostic software might highlight anomalies or offer basic image enhancement tools, but it lacks intelligent analysis capabilities to automatically detect strokes with high accuracy. In terms of patient interaction, existing systems are also not user-centric. They do not provide online access for report viewing on neuroimage interpretation. Current technologies inadequately deliver prompt, automated, and accessible stroke detection help, underscoring the pressing necessity for a more sophisticated, integrated, and user-centric solution.

Current models often struggle with limitations that involve inadequate real-time performance, high computational demands, and challenges in handling data from different imaging sources. To address these concerns, the proposed solution utilizes a CNN built upon the VGG16 architecture an advanced deep learning model originally created by the Visual Geometry Group at Oxford. The architecture is modified by removing its original fully connected layers, transforming it into an efficient feature extractor. A customized binary classification head is then added to differentiate between stroke and non-stroke cases. The terminal output layer comprises a solitary neuron utilizing sigmoid activation, making it ideal for binary classification applications. The model is improved to include both CT and MRI image inputs and is connected with a chatbot, thereby merging high diagnostic precision with an approachable and engaging user interface.

3. Proposed Work

Deep learning methods like edge learning, specifically CNNs, more familiar in medical imaging since they significantly aid in the early detection of conditions like stroke. With an accuracy of over 90% in categorizing CT and MRI images, CNN designs have proven to be quite successful. These models may, however, have issues with overfitting, especially when training on rare data. This issue can be mitigated with the use of transfer learning techniques, such as adapting pre-trained models like VGG16 for medical imaging applications.

The suggested stroke detection system uses DL, especially to speed up and enhance the interpretation of neuroimages such as CNN, CT, and MRI scans based on the VGG16 architecture, as shown in Figure 1. By detecting and identifying stroke-affected areas in the images, the algorithm improves diagnostic precision and reduces the need for human evaluation. To improve major image characteristics, the process begins with several preparation steps, such as grayscale image conversion, histogram equalization, and CLAHE (Contrast Limited Adaptive Histogram Equalization). After preprocessing, the initial dense layers of the VGG16 model are eliminated and used as a feature extractor. To distinguish between stroke examples and general cases, a custom binary classification is applied. The Adam optimizer is used in the training phase, and binary cross-entropy is used as a loss function. Techniques, including data augmentation, class weighting, and early stopping, are used to manage imbalance and to ensure that the model properly generalizes.

A significant advancement of the proposed system lies in its double-interface design: for a medical professional (radiologists) and for a patient. The administrator dashboard enables the provider to review the clinical results and respond to the patient, while the patient interface allows users to access the report and interact with the chatbot. This chatbot acts as an informative accessory, addressing questions related to basic strokes, providing guidance on symptoms, and explaining testing processes, although it does not diagnose therapy. Additionally, the system is supported by a secure SQL database for patient records and report management, in which automatic email notifications are sent to patients when their results are ready, ensuring timely and convenient access to medical information.

The system differs from previous versions by incorporating these capabilities, including an AI-operated chatbot, automated email notifications, and an intuitive interface for patients and healthcare providers. Additionally, the VGG16 architecture is adapted for feature extraction and reduces overfitting, increasing accuracy in sophisticated training methods such as class weighting and dropout. This state-of-the-art structure provides individuals with an easy and effective way to maintain their health while giving health professionals a powerful clinical tool.

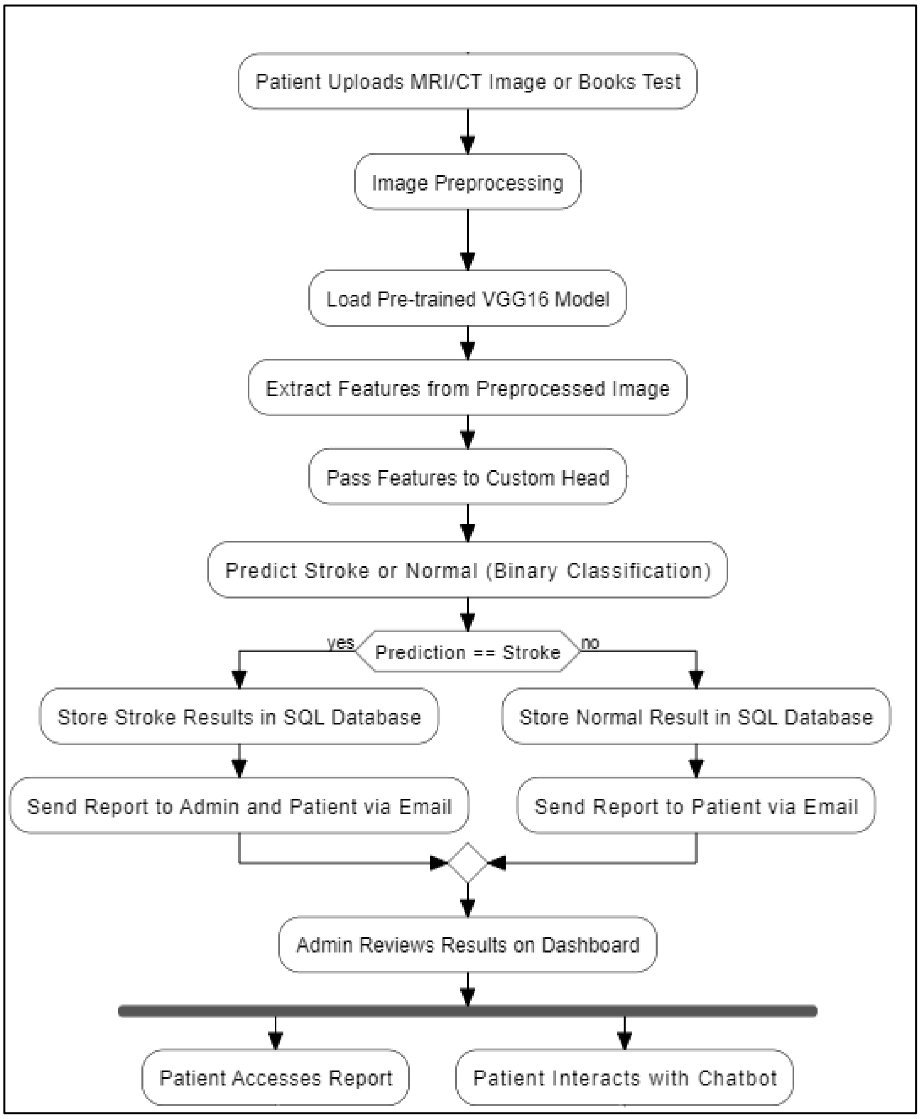

Figure 1. Proposed System

3.1 Data Processing

In the context of machine learning-based image classification, data processing serves as the foundational step to ensure that input data is clean, consistent, and ready for modelling.

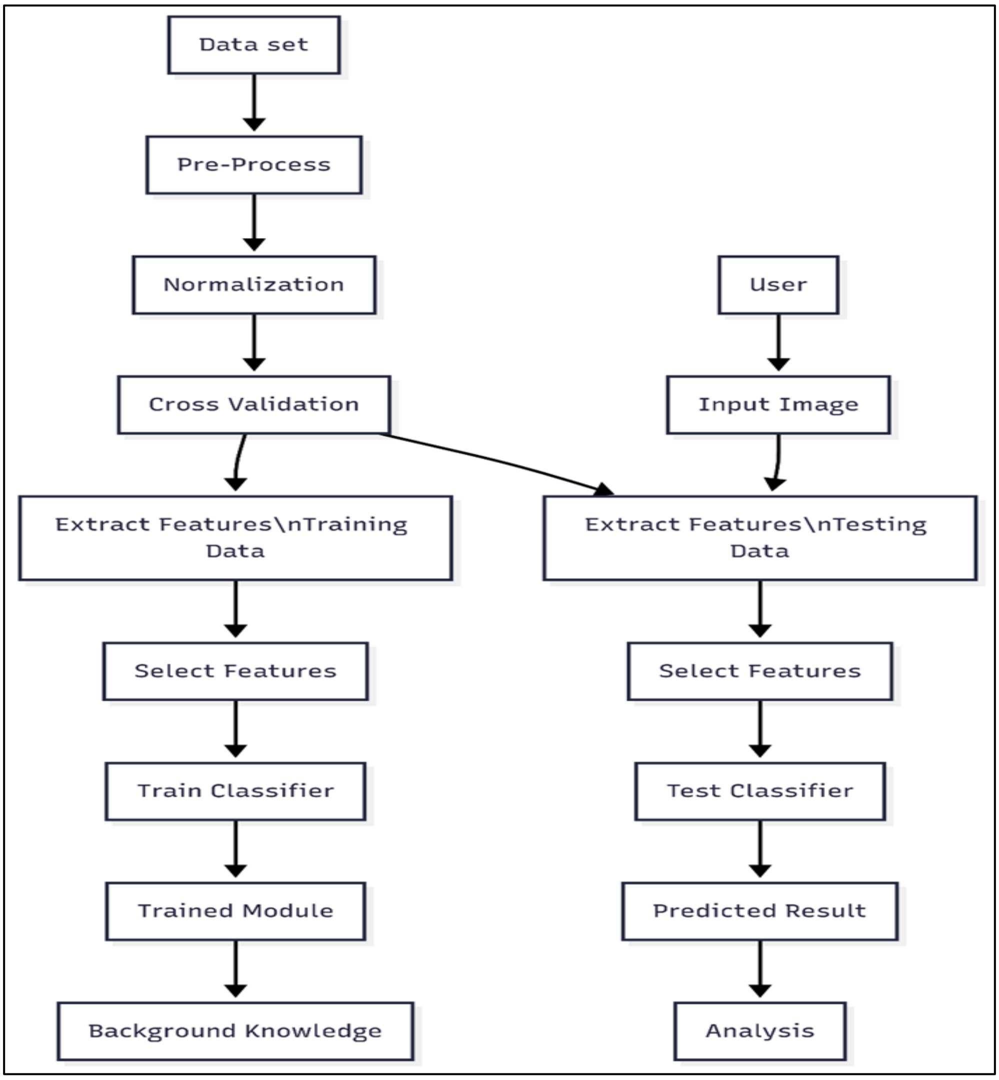

Figure 2. Data Processing

In Figure 2, the process begins with the dataset undergoing pre-processing, which may include removing noise, correcting artifacts, or handling missing or irrelevant data. This is followed by normalization, which scales data into a consistent range, essential for models that rely on numerical stability. The processed data is then split into training and testing sets through cross-validation, ensuring robust model evaluation. During the training phase, feature extraction identifies key patterns or attributes from the images, and feature selection retains the most relevant ones to reduce dimensionality and improve learning efficiency. A classifier is then trained on this curated data, resulting in a trained module that encapsulates learned knowledge. This module is later applied to the testing data, where the same sequence of feature extraction and selection occurs. The classifier then makes predictions based on previously learned patterns. The output is a predicted result that undergoes further analysis to assess performance, accuracy, and clinical relevance. This structured data processing pipeline ensures that the entire system, from raw data input to final result interpretation, is optimized for reliable and interpretable outcomes.

3.2 VGG16 Model

In Figure 3, a deep convolutional neural network originally trained on the large-scale ImageNet dataset. VGG16 is widely recognized for its depth and simplicity, consisting of 13 convolutional layers and 3 fully connected layers arranged in a very uniform architecture. The key advantage of using VGG16 lies in its ability to extract rich hierarchical features from images, which can be transferred and reused for different computer vision tasks beyond the original classification categories in ImageNet. For the purpose of stroke classification in neuroimages, the top layers of the pre-trained VGG16 model, which include the dense classification layers, are removed. This leaves behind the convolutional base, which acts as a robust feature extractor. The convolutional layers are retained in their pre-trained state and are not updated during training. This “frozen” configuration ensures that the valuable general features learned from the large ImageNet dataset, such as edge detectors and texture patterns, are preserved and reused effectively in the new task. Freezing these layers also significantly reduces training time and mitigates the risk of overfitting, especially in domains like medical imaging, where labeled data may be limited.

To adapt the model for binary stroke classification, a custom classification head is added on top of the frozen base. This custom head is designed to learn task-specific patterns from the features extracted by the base model. The first layer in this custom head is a Flatten layer, which transforms the multi-dimensional feature maps from the final convolutional layer into a one-dimensional vector. This flattened representation serves as the input to a fully connected Dense layer consisting of 256 neurons with ReLU (Rectified Linear Unit) activation, allowing the model to learn complex, non-linear combinations of the input features. To further prevent overfitting, especially given the relatively small size of many medical datasets, a Dropout layer is included after the dense layer. Dropout works by randomly disabling a fraction of the neurons during training, forcing the network to develop redundant and generalized feature representations. Finally, the last layer in the custom head is a Dense layer with a single neuron and a sigmoid activation function. This layer outputs a probability value between 0 and 1, representing the likelihood of the input image being associated with a stroke. A probability threshold (commonly set at 0.5) is then applied to determine the final class label: stroke (1) or normal (0). This architecture leverages the strength of VGG16's generalized visual knowledge while enabling specialized learning through a lightweight, trainable head. It provides an efficient and effective framework for applying deep learning to medical imaging tasks such as stroke detection, where domain-specific labeled data may be limited but diagnostic precision is critical.

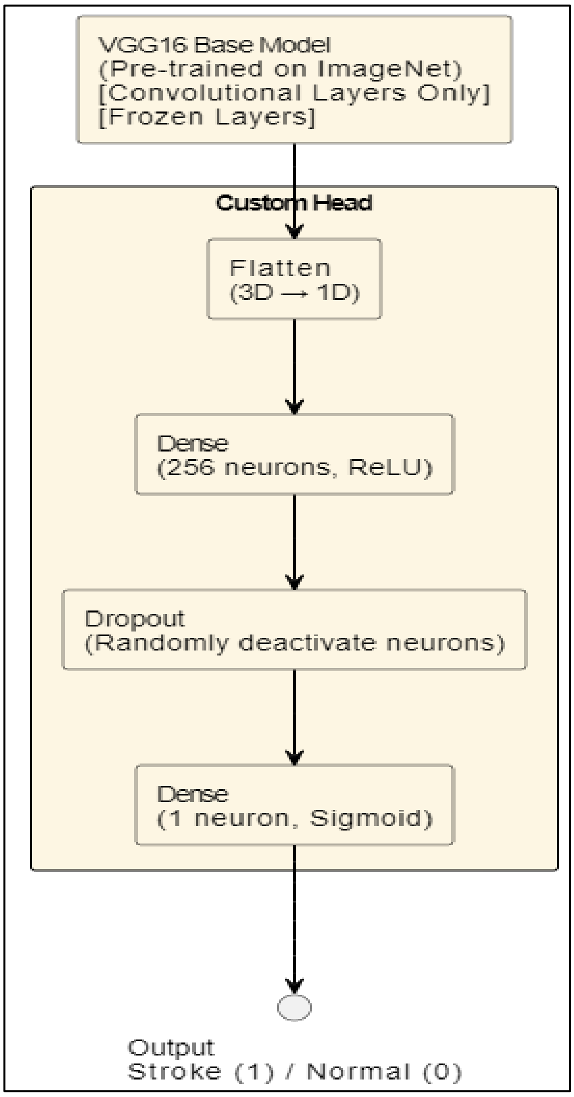

Figure 3. VGG16 Model Transfer Learning Architecture

3.3 Algorithms

Step 1: Increased images and preprosasing

The following preprocessing stages are applied to raw CT and MRI images to guarantee stability and increase clinical accuracy:

- Grayscale conversion: Reduces complexity by converting images into a single-channel format.
- Histogram equalization: Increases visibility of physical characteristics by balancing the histogram.
- Contrast-limited adaptive histogram equalization: Improves localization without increasing noise.
- Gamma correction: Improves feature representation by adjusting brightness.
- Size and normalization: To satisfy the VGG16 input specifications, all images are resized to 224 × 224 pixels and normalized in a [0,1] range.

Step 2: Equality of features applying VGG16 (learning transfer)

The system uses the VGG16 model, which has already been trained, as a foundation for convenience:

To preserve generalized visual features obtained from ImageNet, some layers of VGG16 are frozen.

An additional custom classification is implemented:

- The flattened layer creates a 1D vector from the recovered features.
- ReLU activation is used in the dense layer (256 neurons) for non-linear feature mapping.
- To avoid overfitting, the dropout layer randomly drops neurons during training.
- The output layer has a single neuron that uses binary classification (normal or stroke) with sigmoid activation.

Step 3: Configuring the model for training

The following configuration is used to compile and train the model:

Damage function:

- Binary cross-entropy is suitable for problems associated with two classes.

Optimizer:

- The Adam optimizer, which has a learning rate of 0.0001, was chosen due to its consistent convergence and adaptive performance.

Improvement in training:

- Using an image data generator, data augmentation improves dataset variability (rotation, scaling, and flipping).

Early Stopping:

- To avoid overfitting, this technique prevents validation loss during training.
- The model with the highest validation accuracy is saved using model checkpointing.
- When calculating the damage, class weighting is applied and balances the contribution of non-stroke samples.

Step 4: Model Evaluation and Implementation

Accident, accuracy, recall, F1-score, and AUC are among the metrics used to assess trained models on a separate test dataset.

Next, the model is included in a system with two interfaces:

- Allows patients to upload neuroimages. Radiologists reflect clinical predictions. Reports are emailed, and an AI-Interested Chatbot is used to answer questions.

4. Results and Discussion

With the use of NeuroEmis, a machine learning framework created for stroke detection, excellent performance is achieved in determining if a given case is a test for stroke. The device effectively creates a strategy for identifying stroke signs using the Deep Pandus convenience and the VGG16 Convolutional Neural Network with pre-processed MRI and CT images. State-of-the-art pre-processing techniques, gamma enhancement, generalization, and model integration also improve the quality of performance and images. The test results verify that the model predicts various input records accurately and consistently. Furthermore, radiologist scan review and manage cases with ease due to the user-friendly platform, which enables patients to upload scans and receive results. Accessibility and customer engagement are improved through the use of chatbot integration features and email reports. Overall, the technique shows promise in helping to detect strokes early and saving medical staff money.

This version enables medical personnel to provide short-term solutions and improve patient outcomes by demonstrating and displaying abnormal integration capabilities in medical decision-making systems. Figure 4, displays the home page of the web interface. This user serves as the entry point, providing radiologists and patients access to the login and registration portal. The design prioritizes safe access and user-friendly facilities for the system.

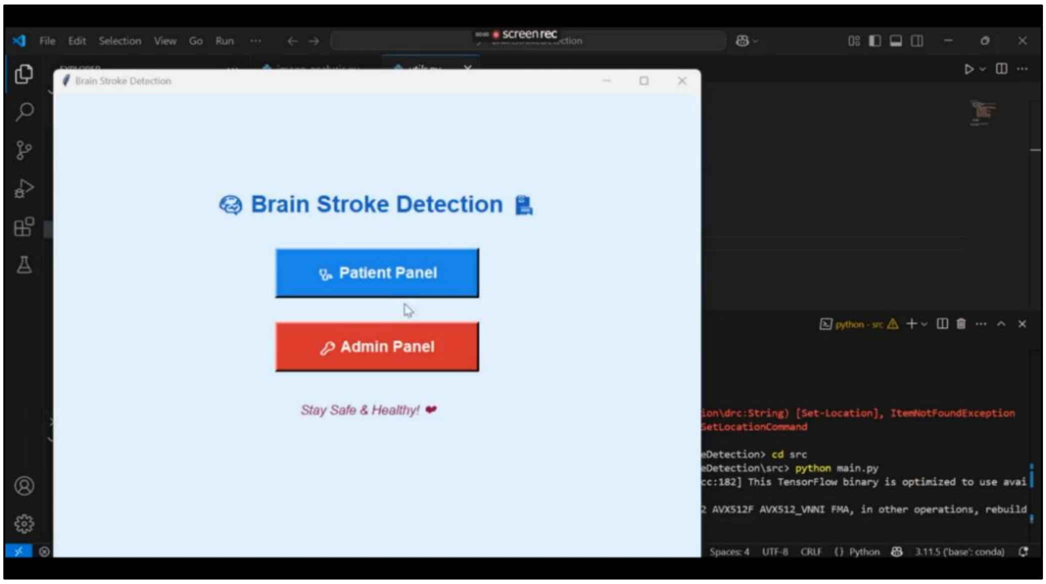

Figure 4. Home Page

The patient dashboard is shown in Figure 5 where users can examine clinical findings, upload neuroimages for analysis, and communicate with chatbot to learn more about stroke - related symptoms and procedures.

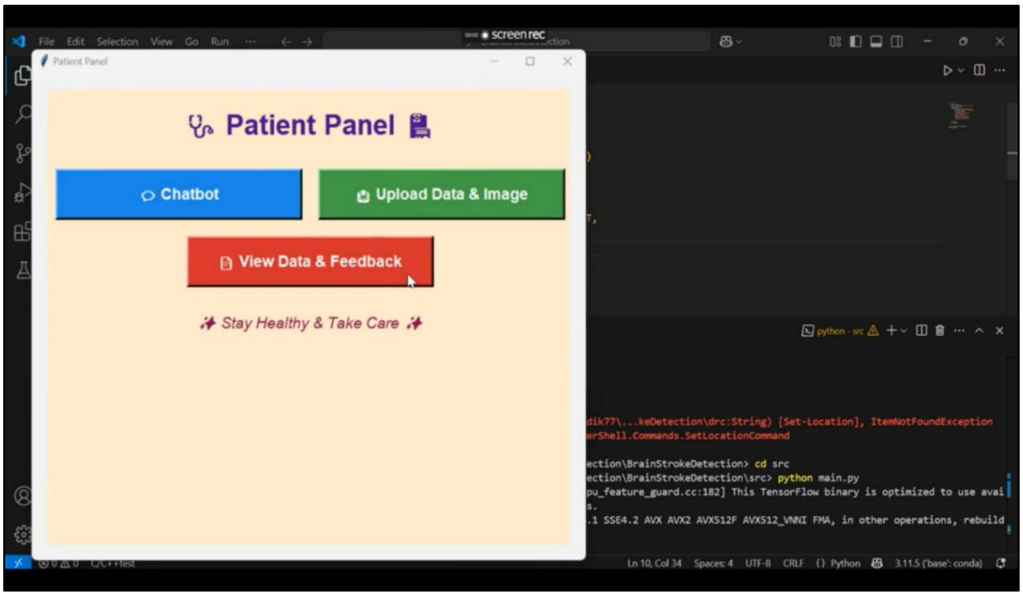

Figure 5. Patient Panel

In Figure 6, New users can create an account using registration form. To guarantee that the access control is retained on the entire platform, it collects the necessary credibility and roles (patient or doctor).

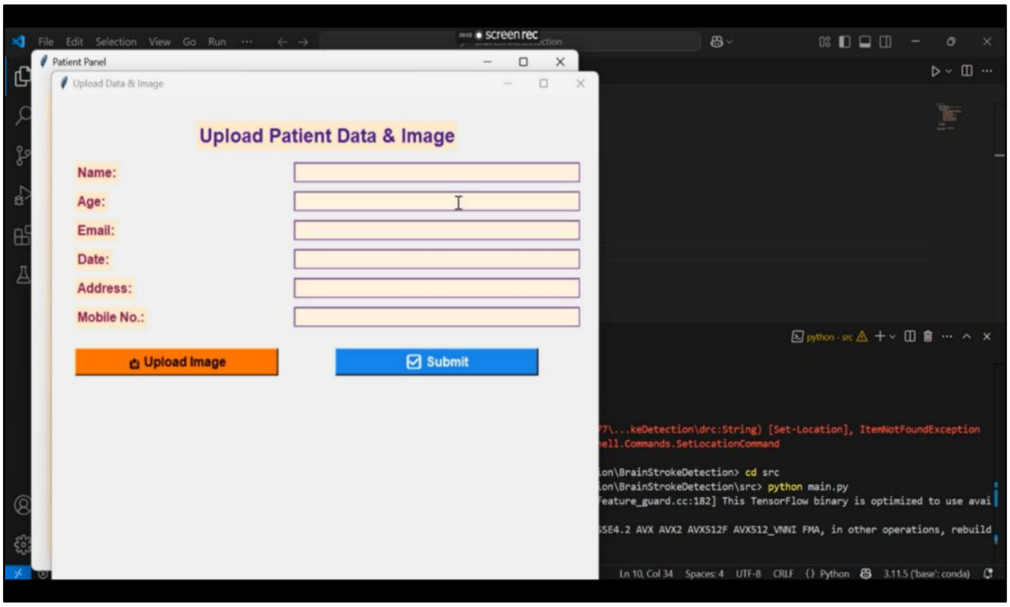

Figure 6. User Register

In Figure 7, Radiologist or patients can upload CT or MRI scans using this interface. The AI model then prepares and classifies uploaded photos. Quick and simple interaction with the clinical pipeline is ensured by this feature.

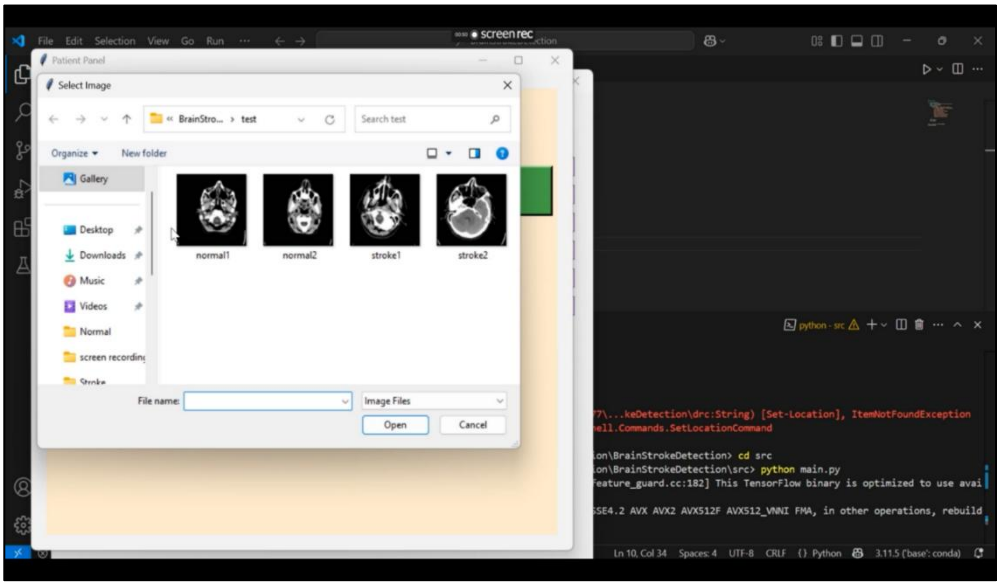

Figure 7. Upload Image

By answering frequently asked questions about strokes, the chatbot provides non-mentholated assistance. Overfitting this patient increases awareness and participation; however, this specialist cannot replace medical guidance, as shown in Figure 8.

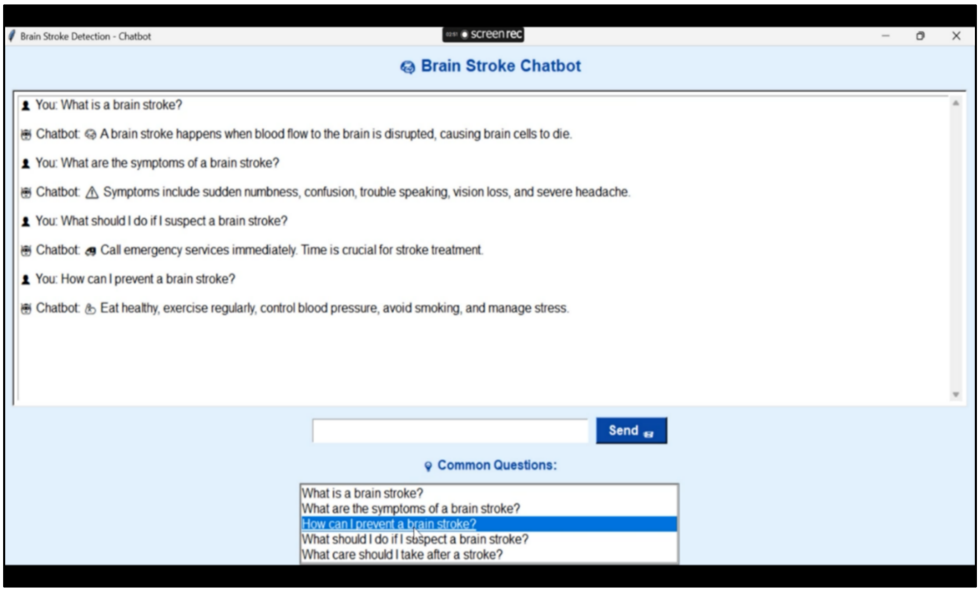

Figure 8. Chatbot

An alternative Figure 9, home page scene that can be adapted to a separate role allows for amendments according to access privileges, guaranteeing uniformity between jobs.

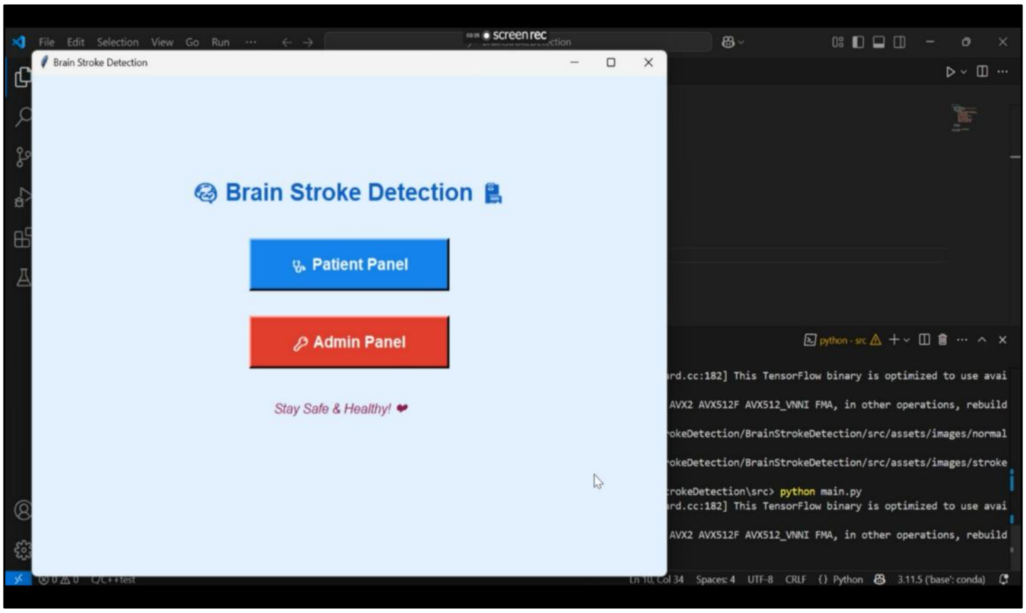

Figure 9. Home Page

In Figure 10, Radiologist can use patient records, image analysis results, and reaction mechanisms through this panel. For clinical users, it centralizes all clinical resources.

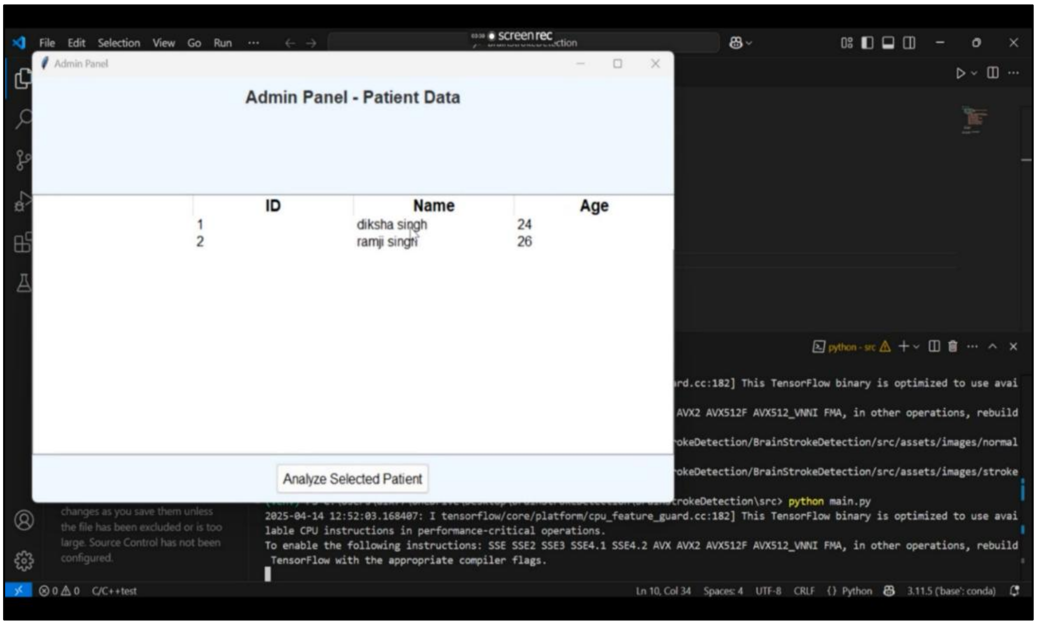

Figure 10. Admin Panel

In Figure 11, Radiologist can check classifications produced by AI, provide comments, or validate results. This loop enables specialist verification and enhances the system's trust.

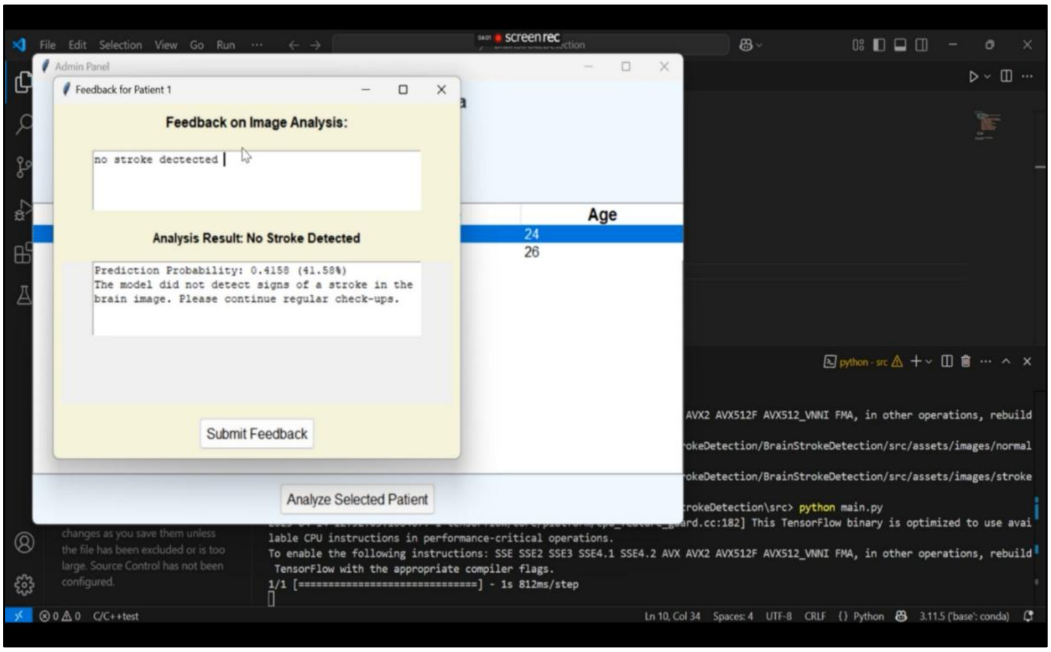

Figure 11. Feedback On Image Analysis

With the use of this function, the doctor can select a special patient and check the scan uploaded with details shown in Figure 12.

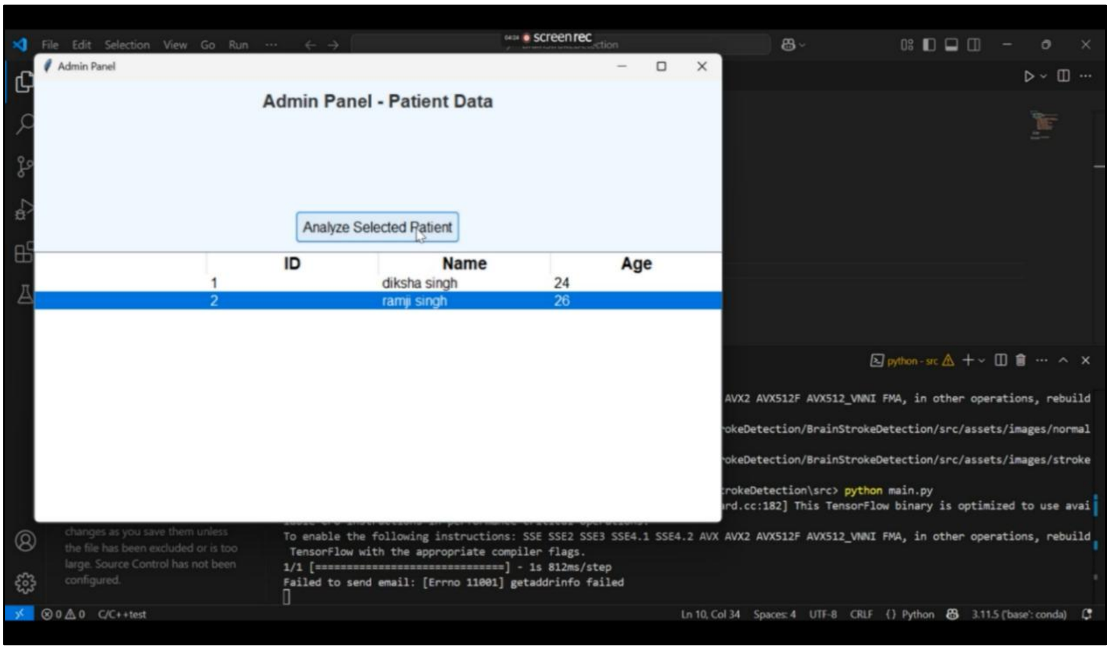

Figure 12. Analyse Selected Patient

The Figure 13 automatic email exhibits the facility that allows patients to achieve their prepared clinical results safely. This guarantees early documentation and communication.

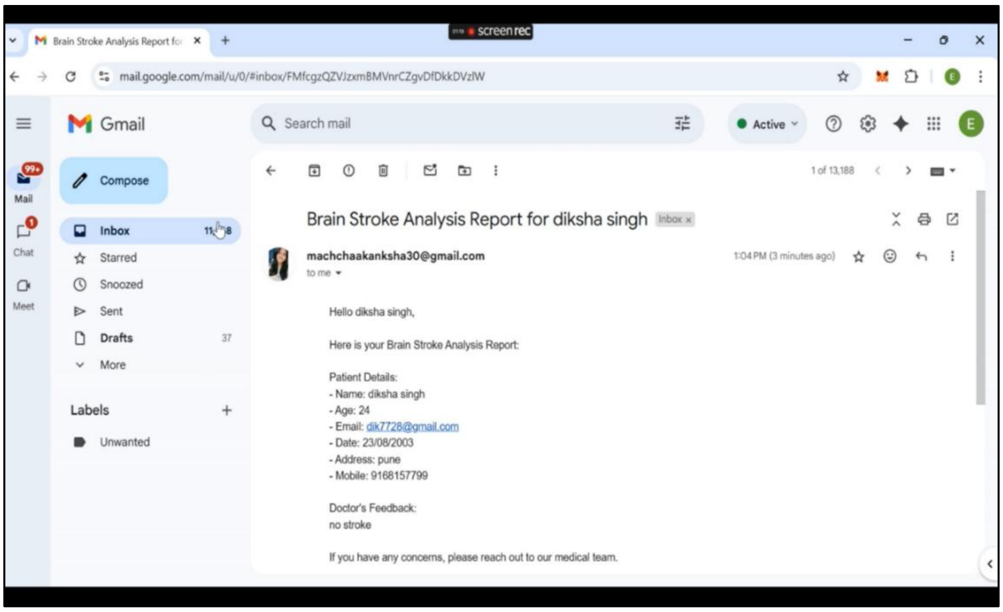

Figure 13. Report Received Through Mail

A summary scene that displays the uploaded photographs, analytical comments, clinical results and history of patient contacts. It facilitates the patient's follow-up as well as the audit shown in Figure 14.

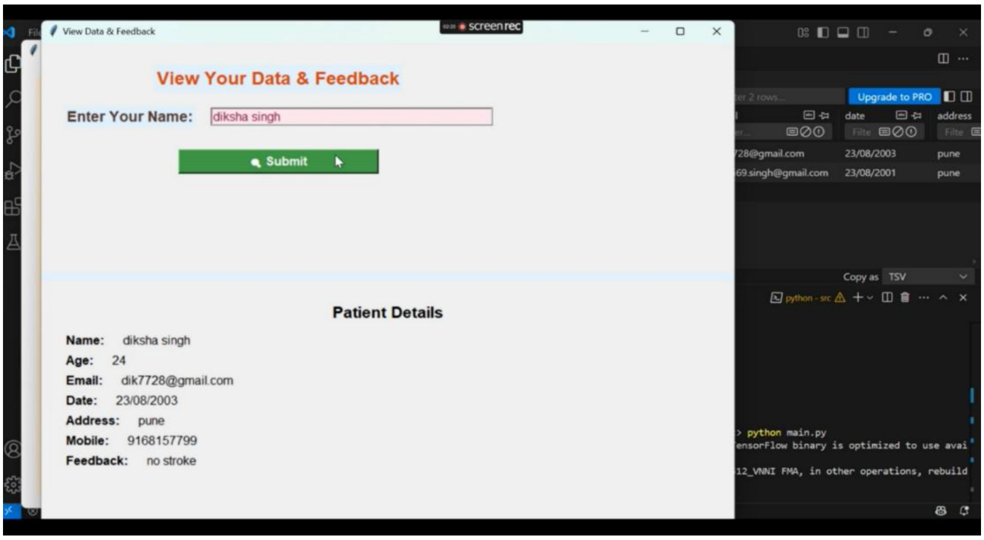

Figure 14. View Data & Feedback

5. Conclusion

In conclusion, the suggested stroke detection framework clearly indicates how CNNs, notably VGG16, can be used in medical imaging to aid in early stroke diagnosis. The technique gives medical practitioners a reliable, automated means of interpreting CT and MRI scans, allowing them to make accurate diagnoses quickly. It is intended to be user-friendly for both patients and physicians, with capabilities such as image uploads, report generation, and chatbot support. Because it reduces reliance on manual reading and speeds up diagnostics, this paradigm has great potential for use in clinical practice and telemedicine, resulting in quicker interventions and better patient outcomes.

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