Detection of Hemorrhagic Brain Arteriovenous Malformations using ML

Soham Devikar[1], Simranjeet Singh[2*], Sushil Deshmukh[3*], Dr.D.M.Bhalerao[4*]
[1234*], Electronics and Telecommunication, Sinhgad College of Engineering, Pune, India

Abstract:- The project's purpose is to develop and improve emergency healthcare services for the rapid and reliable diagnosis of brain bleeding. The conventional approach of manual reviewing of CT and MRI scans is tedious and error-laden. Our method employs Convolutional Neural Networks (CNNs) for feature extraction, combined with Support Vector Machines (SVMs) for classification yielding a 97% average accuracy. To enhance the experience for the users, there is also a chatbot powered by Natural Language Processing (NLP) that aids patients and healthcare professionals in navigating through the diagnosis and the follow-up actions. The efficiency of AI and NLP ensures not only improved diagnostic speed and accuracy, but also assists in real-time scalable solutions for emergency care.

Keywords:- Brain Arteriovenous Malformation , Convolutional Neural Network(CNN), Machine Learning (ML), CT/MRI Scan Analysis, Chatbot Assistance, Support Vector Machine(SVM).

1. INTRODUCTION

Our study is centered on the creation of an AI based technology for the precise and prompt identification of brain hemorrhages from MRI and CT scan images. The system employs Convolutional Neural Networks (CNN) for feature extraction and classification with a Support Vector Machine (SVM) achieving average detection accuracy of 97% which minimizes manual interpretation dependency.

In order to help the users get real time assistance, the system has integrated a basic chatbot that is driven by Natural Language Processing (NLP) that not only answers user queries but also explains medical jargon and provides instruction based on the user provided analysis outcome. This initiative attempts to bridge the gap between developed medical imaging techniques and the imaging diagnostic tools by enabling its use in emergency medicine, telemedicine, and clinical medicine.

2. LITERATURE SURVEY

The "An Attention-Based ResNet Architecture for Acute Hemorrhage Detection and Classification: Toward a Health 4.0 Digital Twin Study" in 2022 used the RNSA-2019 dataset, preceded by minority class balancing through data augmentation. The approach of preprocessing of augmented CT scans, feature extraction employing an attention-based ResNet-152V2 model, dimensionality reduction with PCA, and classification with the XGBoost algorithm for intracranial hemorrhage detection. Inspired by this methodology, our project uses CNN for efficient feature extraction and SVM for precise classification, solving generalization and overfitting with optimization methods.

In 2019, the research paper "An Ensemble Learning Approach for Automatic Brain Hemorrhage Detection from MRIs" presented a technique that starts with preprocessing to segment the brain region from the skull. This is then followed by feature extraction to determine meaningful features from MRI scans, which are subsequently utilized to train an adaptive boosting algorithm. Detection and annotation steps further improve the accuracy of hemorrhage detection. This ensemble learning approach informed our project's hybrid model design that combines deep feature extraction with strong supervised classifiers to obtain accurate real-time clinical image interpretation.

Furthermore, in the 2020 research titled "Machine Learning Application With Quantitative Digital Subtraction Angiography for Detection of hemorrhage brain arteriovenous Malformations," they highlighted feature selection methods like Chi-Squared, MRMR, ReliefF, and t-Test to preprocess and purify input data. Various machine learning algorithms like Random Forest, Naïve Bayes, and SVM were explored for classification purpose, and the hyperparameter adjustment was performed via Bayesian Optimization and 5-fold cross-validation. This holistic strategy motivated our combination of CNN for deep spatial feature learning and SVM for classification with the goal of achieving a good balance between accuracy and computational efficiency in real-time CT image analysis.

3. METHODOLOGY

3.1 SYSTEM ARCHITECTURE

The illustration shows a mechanism for identifying brain hemorrhage based on an input image. Preprocessing and extraction of features in the image happen, followed by CNN and SVM algorithms to identify the features to match against the trained data. Depending on the output, the system identifies the presence of brain hemorrhage or not and produces the output with chatbot interaction.

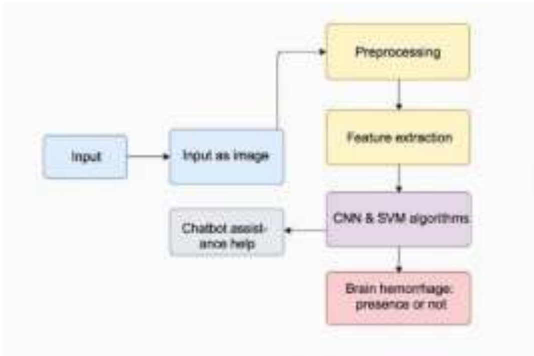

Fig 3.1.1. System Architecture

PREPROCESSING

The purpose of pre-processing is to distinguish the pattern of interest from the background by removing the irrelevant data present in the scanned image.

1. RESIZE IMAGE

Resizing is a fundamental operation during image preprocessing. It is required for display, storage and transmission of the images. Resizing is changing the size of an image. It is done due to the fact that it fits on the system user interface. The gray scale image, after conversion, is resized to 64 pixels by 64 pixels in size.

2. CONVERSION OF GRAYSCAL

CT image is converted into gray scale image in order to make it contrast. Contrast image helps in delivering accurate information regarding the tissues.

3. EDGE DETECTION & SHARPENING

Edge detection is referred to as identifying and determining the position of sudden discontinuities in a provided image. Edges are actually object surface boundaries that are likely to produce oriented, localized intensity variations of an image. Sobel operator is used for edge detection in this system

3.2 MODEL TRAINING

Training the model, morphological image processing assists in the improvement of the shape-based features in medical images, particularly in binary or grayscale images. The CNN is employed to extract features automatically using convolutional layers, activation functions such as ReLU, and spatial reduction pooling layers. The features are flattened and fed to the SVM classifier. The dataset is divided into training and validation sets, in which the CNN is trained to extract useful features and the SVM is trained to classify them as hemorrhagic or not. Hyperparameter optimization, including the SVM's regularization tuning, is performed using cross-validation. Also, contour-based features such as object number, area, and image energy are examined to enhance classification accuracy by giving insights into hemorrhage type and severity.

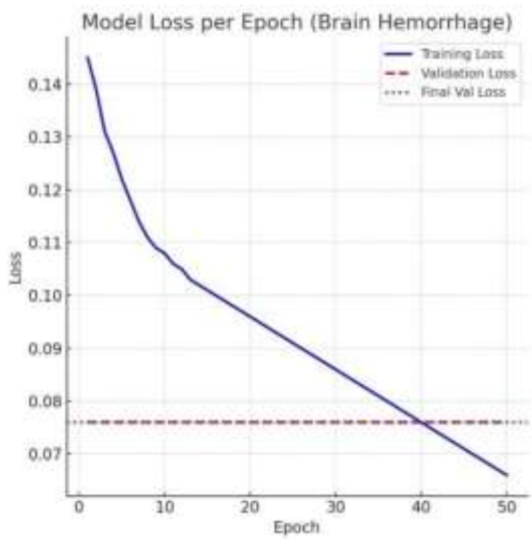

Fig. Loss cruves for Brain hemorrhage detection model

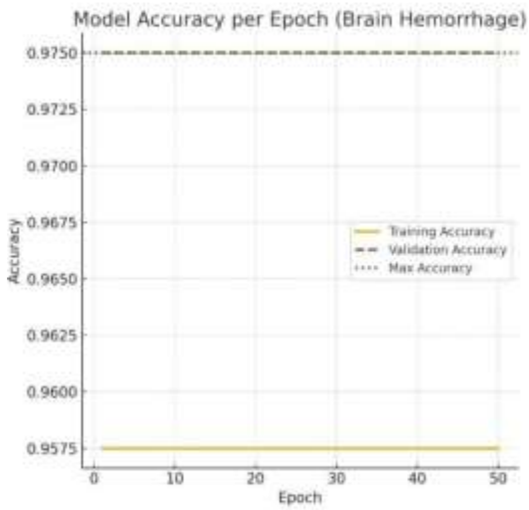

Fig. Training and Validation accuracy

3.3 REAL TIME HEMORRHAGE DETECTION

In real-time hemorrhage imaging, the pre- processed input brain scan (mri or ct) is input into a trained cnn model first, which directly extracts key features like edges, textures, and patterns associated with hemorrhages instantaneously. the features are then flattened and used as input into a pre-trained svm classifier, which rapidly identifies whether the image depicts hemorrhagic or non-hemorrhagic areas. the model is tuned to provide rapid and precise results by reducing latency in feature extraction as well as classification. further real-time examination of contour-based features—such as the count of bleeding areas (objects), their size, and image energy—yields instant information about the nature and severity of the

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hemorrhage. the system has the potential to aid medical personnel by providing quick, automated evaluations in emergency rooms, enhancing diagnostic speed and decision-making.

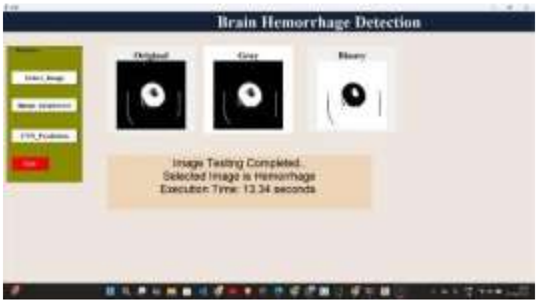

Fig3.3.1 Normal Brain Detection

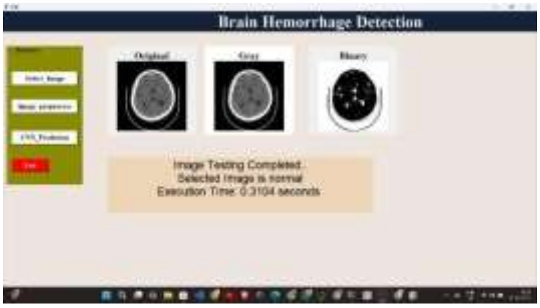

Fig.3.3.2 Brain Hemorrhage Detection

3.5 RESULT AND DISCUSSION

The chosen hardware raspberry pi adequately interfaced with desktop monitor and mouse and software components. Code output we have performed until now displays proper grey scale area, binary area. That offers the perfect representation of brain which summarize that whether hemorrhage is present or not.

The selected algorithm also depicts time taken to execute entire process. The integration of the chatbot in the project assists the user interaction in making project more user-friendly

4. DETECTION ACCURACY

The model had a final training accuracy of 97.54% and validation accuracy plateaued at approximately 62.96%, reflecting extreme overfitting. Previous training had moderate overfitting as well, with 82% training and 72% testing accuracy. While the model learned efficiently from training data, its lower validation performance reflects restricted generalization. For increased detection accuracy on unseen data, methods such as data augmentation, dropout, or model fine-tuning can be utilized

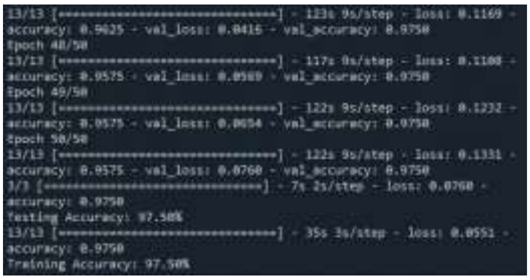

Fig.4.1 Accuracy

CONCLUSION

The Brain Hemorrhage Detection project aims to provide fast and accurate diagnosis by using CNN for feature extraction and SVM for classification, reducing the possibility of human error. It allows physicians to decide on treatments more quickly, especially in critical cases. It reduces the burden on healthcare workers by automating image analysis. The chatbot that is integrated into the system enhances patient interaction and provides information in real time. Overall, the system supports enhanced patient care, streamlined processes, and smart use of hospital resources.

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