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Facial Stroke Recognition System using Machine Learning Techniques

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Abstract: The detection of facial stroke symptoms can be significantly enhanced using the Convolutional Neural Network (CNN) algorithm, a robust deep learning approach for image analysis. CNNs are particularly well-suited for identifying patterns and abnormalities in facial images, such as asymmetry, drooping muscles, or irregular movements associated with stroke. by training the network on a diverse dataset of facial images, the model learns to differentiate normal and stroke- affected features with high accuracy. This automated detection system can process real-time video streams or static images, providing quick and reliable assessments. The use of CNNs in facial stroke detection not only improves diagnostic efficiency but also holds. the potential to facilitate early interventions, especially in remote areas where medical expertise is limited. This technology represents a significant advancement in the intersection of health care and artificial intelligent

Keywords: Machine Learning; Convolutional neural network (CCN); Random Forest Algorithm

I. INTRODUCTION

Stroke is a leading cause of death and long-term disability worldwide, often resulting in significant physical and neurological impairments. Early detection and timely medical intervention are critical in minimizing the adverse effects of a stroke. Facial asymmetry, particularly in the form of drooping or uneven muscle control, is one of the most visible and early signs of stroke. However, manual identification of these symptoms is prone to error and subjectivity, especially in high- stress or remote environments.

Recent advancements in machine learning (ML) and computer vision have enabled automated systems capable of detecting subtle facial anomalies with high accuracy. These technologies offer a promising avenue for developing real- time, accessible, and reliable stroke recognition tools. A facial stroke recognition system powered by ML can analyze facial features, identify abnormal patterns, and assist healthcare professionals or even non-specialist users in recognizing the onset of stroke symptoms.

This paper proposes a machine learning-based facial stroke recognition system that leverages facial landmark detection, feature extraction, and classification algorithms to identify signs of stroke from facial images or video input. By integrating modern ML techniques with facial analysis, the system aims to provide a low-cost, non-invasive solution for early stroke detection, particularly in under-resourced or remote areas. The proposed approach is evaluated using standard datasets and custom image inputs, demonstrating promising results in terms of accuracy and response time. Stroke is a major global health concern, responsible for millions of deaths and disabilities each year. According to the World Health Organization (WHO), stroke is the second leading cause of death globally and a primary cause of long- term disability. Timely identification and intervention are essential for improving outcomes, yet many patients do not receive immediate care due to delays in recognizing the symptoms.

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One of the most common and early indicators of stroke is facial asymmetry**,** such as drooping on one side of the face. However, human error and lack of medical expertise—especially in rural or under-equipped areas—often hinder early diagnosis. The use of machine learning (ML) and computer vision provides a powerful alternative by automating the detection process, reducing subjectivity, and enabling real-time stroke assessment.

This paper presents a Facial Stroke Recognition System based on ML techniques, aimed at detecting facial abnormalities that may indicate stroke. The system utilizes facial landmark detection, feature extraction, and classification models to evaluate facial symmetry and expressions. Through image or video input, the model detects key facial points and computes geometric features such as angles, distances, and facial ratios to determine anomalies.

II.METHODOLOGY

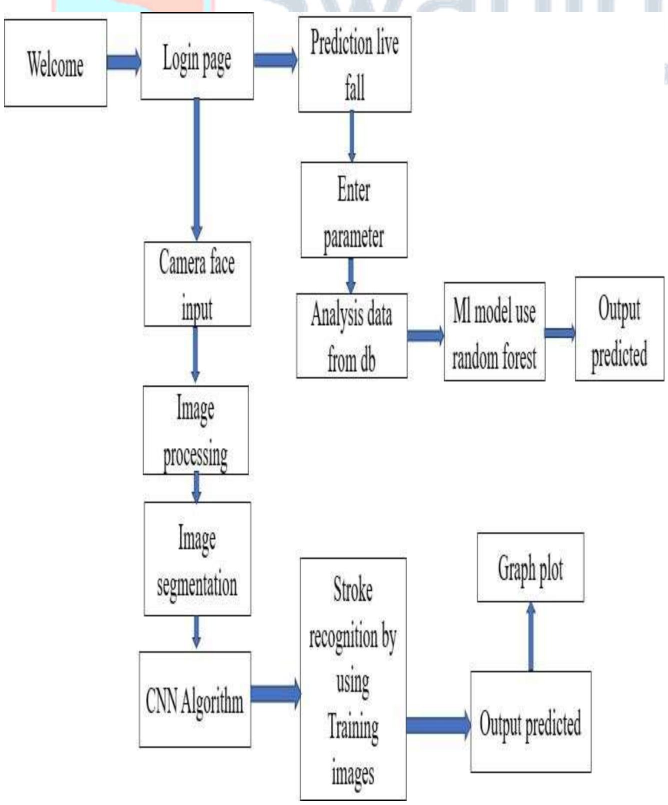

Fig 1 Block Diagram

III. SYSTEM ARCHITECTURE DESCRIPTION

The proposed facial stroke recognition system is designed to detect stroke symptoms from facial input using a combination of image processing, convolutional neural networks (CNNs), and machine learning classifiers.

The architecture is illustrated in Figure1 and explained below:

1. ***Welcome:*** This is the initial interface presented to the user, introducing the application and preparing them for interaction.

2. ***Login Page:*** A secure login interface that authenticates users and allows access to the main system. This step ensures user-specific data privacy and session management.

3. ***Camera Face Input:*** Once logged in, the system activates the device's camera to capture a live facial image or video stream. This input serves as the primary data source for the stroke detection process.

4. ***Image Processing:*** Captured images undergo pre- processing, including operations such as grayscale conversion, noise reduction, contrast enhancement, and normalization. These steps improve image quality and standardize input for further analysis.

5. ***Image Segmentation:*** Segmentation is applied to isolate key facial regions (e.g., eyes, mouth, cheeks). This facilitates focused analysis and improves the accuracy of stroke detection by localizing asymmetries or muscle drooping.

6. ***CNN Algorithm:*** A Convolutional Neural Network (CNN) is employed to extract deep features from the segmented facial regions. CNNs are effective at capturing spatial hierarchies and patterns, making them well-suited for facial analysis.

7. ***Stroke Recognition by Using Training Images:*** The CNN model is trained using labelled datasets containing stroke- affected and healthy facial images. During inference, extracted features are compared against this trained model to classify the input as normal or stroke-affected.

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***8. Output Predicted**:* Based on the CNN's decision, the system provides a prediction result—indicating whether a stroke is suspected. This output is presented to the user along with confidence scores.

9. Graph Plot: The prediction results can be visualized through graphs to show classification probabilities, temporal variations, or comparisons across multiple inputs. This aids in better interpretation for clinicians or users.

10. Prediction Live Fall: This module supports an additional use case—predicting fall risk in stroke patients. Users can enter physiological or movement parameters relevant to fall detection.

11. Enter Parameter: The user manually enters fall-related data (e.g. Age, gender, heart disease, Hypertension, BMI etc…). This input is analysed in parallel to the facial stroke detection module.

12. Analysis Data from DB: The entered parameters are matched with historical data stored in a database. This analysis helps to identify patterns or abnormalities associated with falls in stroke-affected individuals.

13. ML Model Use Random Forest: A Random Forest classifier is used for fall risk prediction. It analyses the entered and historical data to predict whether the patient is at risk of falling, offering a secondary diagnosis.

14. Output Predicted (Fall Risk): The system outputs the result of the fall risk assessment, assisting caregivers or clinicians in taking preventive actions for patient safety.

III.IMPLEMENTATION

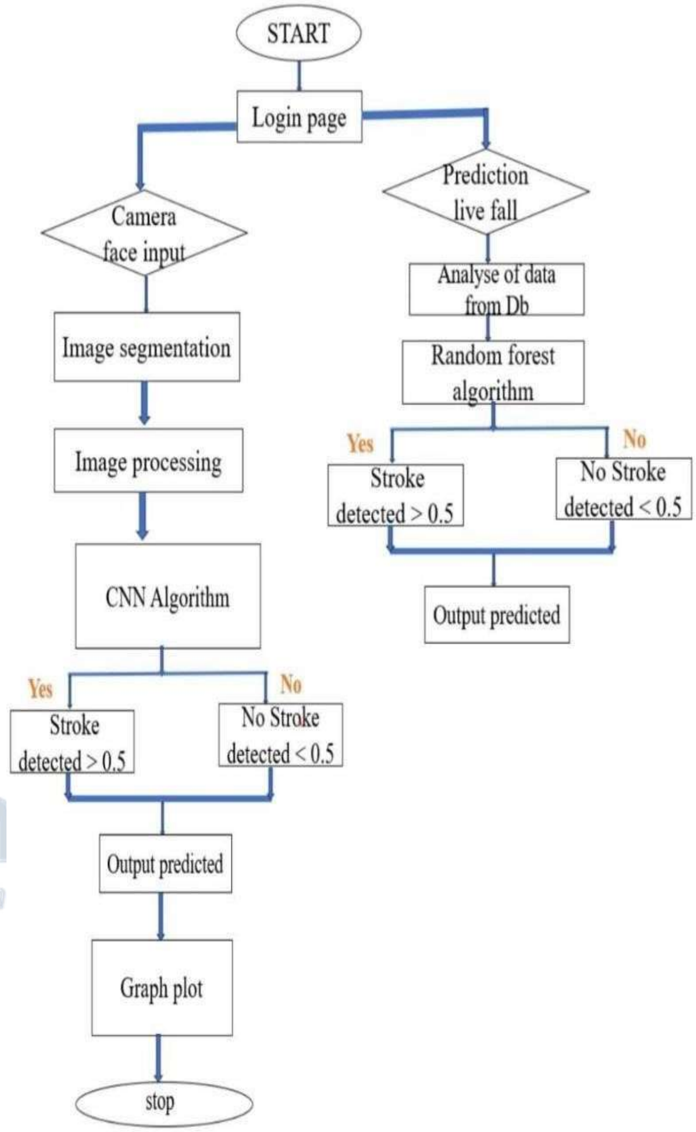

Fig 2 Flow chart

IV. SYSTEM OVERVIEW

The proposed system integrates facial analysis and data-driven prediction to identify potential stroke symptoms in users. As illustrated in Figure 2, the system initiates at a secure login interface and then branches into two primary modules: Facial Stroke Detection and Live Fall Prediction.

In the Facial Stroke Detection module, the user's face is captured through a camera interface. The captured

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image undergoes segmentation to isolate facial regions and subsequent preprocessing to enhance visual features. These processed features are analyzed using a Convolutional Neural Network (CNN)**,** which has been trained on labeled facial datasets. Based on the model's confidence score, the system classifies the face as exhibiting stroke symptoms (if the score is greater than 0.5) or not. The prediction is displayed and also visualized using a graph plot for further insight.

The Live Fall Prediction module works in parallel, where users input physical or behavioral parameters. These inputs are cross-referenced with historical data stored in a database. A Random Forest algorithm processes this information to assess the risk of stroke-related fall behavior. If the predicted probability exceeds the threshold, a stroke warning is issued; otherwise, the user is marked as not at risk. This dual-brancharchitecture provides a comprehensive, real-time analysis by combining visual cues with behavioural data.

V. RESULT ANALYSIS

The results of this project highlight the effectiveness of Convolutional Neural Networks (CNNs) in detecting facial stroke symptoms with high accuracy. By training the model on a diverse dataset of facial images, the system successfully identified stroke-related abnormalities such as asymmetry, muscle drooping, and irregular facial movements. The CNN- based model demonstrated excellent performance in both static image analysis and real-time video stream processing, providing quick, reliable assessments for timely intervention. Additionally, the system's automated nature makes it scalable and accessible, especially in remote areas where medical expertise is limited, enabling early detection and potentially improving patient outcomes. These findings validate the potential of CNNs in revolutionizing stroke diagnosis, offering an efficient, cost-effective solution for early intervention in diverse healthcare settings.

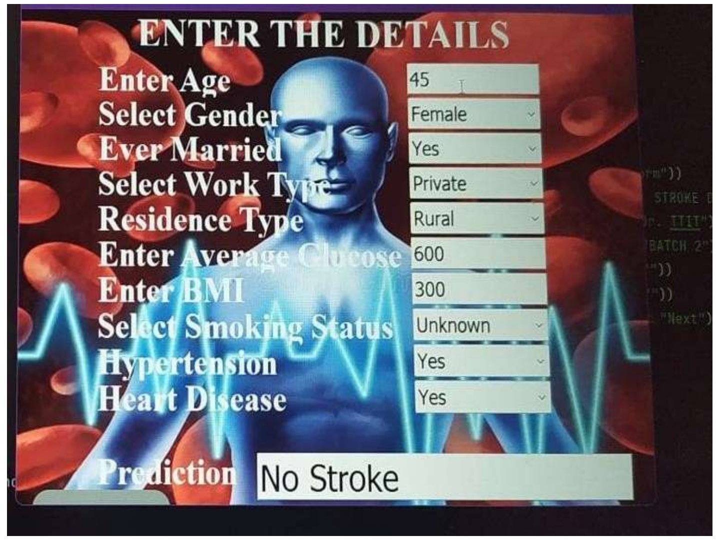

Fig 3 No Stroke with range 0.46

The image shows the user interface of the **stroke prediction module** from the developed system.

This interface allows users to input various health and demographic parameters required for stroke risk analysis. The form includes fields such as Age, Gender, Marital Status, Work Type, Residence Type, Average Glucose Level, BMI (Body Mass Index), Smoking Status, Hypertension, and Heart Disease status. After the user submits these values, the system processes the data using a machine learning model—specifically a Random Forest classifier—which then calculates the probability of stroke occurrence.

In this particular instance, the inputs indicate a 45-year-old female, married, working in the private sector, residing in a rural area, with an average glucose level of 600 and a BMI of 300. Despite having both hypertension and heart disease, the system's prediction result shows "No Stroke" based on the computed probability value (0.46), which is less than the 0.5 decision threshold. This demonstrates the system's functionality in integrating user-specific health data to provide real-time stroke risk prediction, aiding in early diagnosis and prevention.

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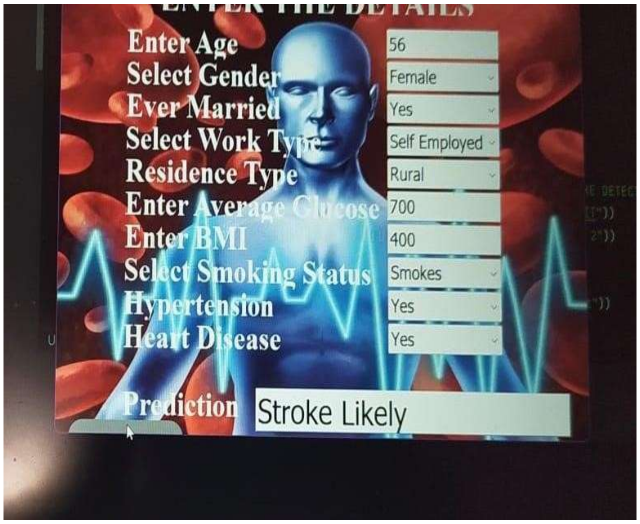

Fig 4 Stroke Likely with range 0.53

The image displays a positive stroke prediction scenario using the machine learning-based stroke detection system.

Here, the user interface has been filled with high-risk health indicators: a 56-year-old female who is married, self- employed, resides in a rural area, has a very high average glucose level of 700, a BMI of 400, and is a smoker. Additionally, the user has both hypertension and heart disease. Based on these critical input parameters, the Random Forest model processes the data and computes a stroke risk probability score that exceeds the threshold of 0.5. Consequently, the system generates a "Stroke Likely" prediction, which is clearly displayed to alert the user or clinician.

This result illustrates the system's ability to integrate multiple clinical and lifestyle factors into an accurate stroke risk assessment, which can significantly aid in preventive healthcare, early intervention, and decision-making. Such real-time visual feedback also enhances the usability of the application in healthcare settings.

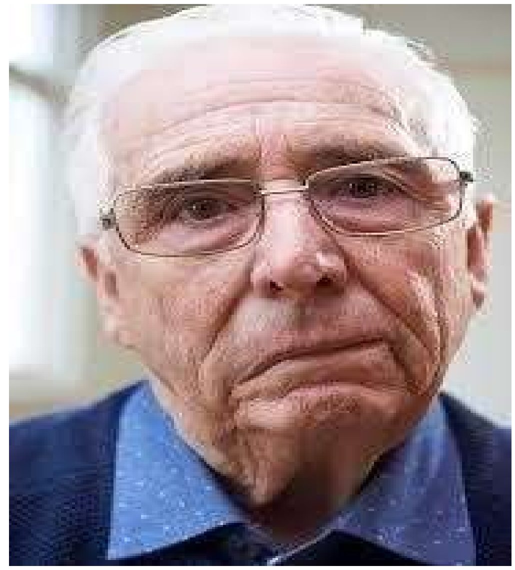

Fig 5 Stroke Likely

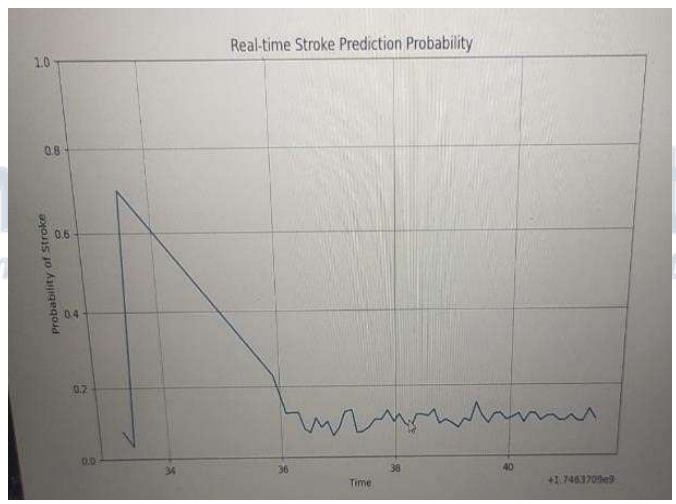

Fig 6 Graphical representation of person with stroke

The graph illustrates a real-time stroke prediction probability for an individual over a short time period. Initially, the probability of stroke spikes sharply to above 0.6, suggesting a high-risk state. However, this is immediately followed by a rapid drop and a continued downward trend in the probability, stabilizing around 0.1 to 0.2. This fluctuation may indicate that the system initially detected a possible stroke risk— possibly triggered by abnormal or extreme input values (such as elevated glucose or blood pressure)—but as additional data was processed (e.g., from facial inputs, vital signs, or

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updated user parameters), the algorithm adjusted its prediction downward, likely ruling out stroke.

Such a pattern may reflect a scenario where the individual exhibited transient risk factors or artifacts in the data that were later corrected or normalized.

Fig 7 No stroke

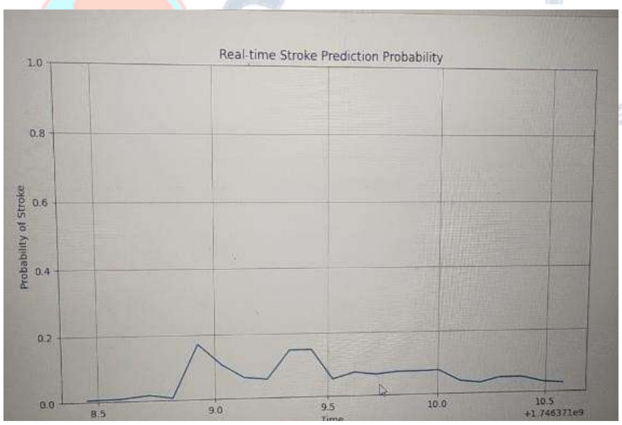

Fig 8 Graphical representation of person with no stroke

This graph represents a real-time stroke prediction probability over a specific time frame for an individual. The prediction values remain relatively low throughout, with probabilities ranging between 0.05 and 0.2, indicating a consistently low risk of stroke during this monitoring window. There are a few minor fluctuations particularly small spikes around the 9.0 to 9.5 time mark but these do not cross the critical threshold (typically 0.5), which would suggest a high probability of stroke.

Such a pattern indicates the person being monitored is not at immediate risk, and any detected variations are likely within a safe physiological range or may reflect transient, non- critical changes in health parameters.

VI. CONCLUSION

Convolutional Neural Networks (CNNs) are highly effective in analysing facial images to detect stroke-related abnormalities such as facial asymmetry, muscle weakness, and drooping— common indicators of a stroke. When integrated with patient-specific health data like Body Mass Index (BMI), heart disease status, and hypertension history, the system becomes even more powerful and personalized. These additional clinical features provide crucial context, helping the model distinguish between facial expressions caused by stroke and those resulting from other conditions. For instance, a high BMI may indicate obesity, which is a risk factor for both ischemic and haemorrhagic strokes. Hypertension (high blood pressure) is a leading cause of strokes as it can lead to blood vessel damage in the brain, while heart disease increases the risk of clots that may travel to the brain.

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