



# SMART HEALTHCARE SYSTEM FOR MULTI-MODAL STROKE PREDICTION

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## ABSTRACT

Stroke is one of the leading causes of mortality and long-term disability worldwide, necessitating early and accurate prediction for effective prevention and treatment. Traditional stroke prediction methods often rely on limited clinical parameters, resulting in reduced accuracy and delayed diagnosis. This project proposes a multi-modal stroke prediction system that integrates heterogeneous data sources such as medical imaging (MRI/CT scans), electronic health records (EHR), genetic information, and lifestyle factors to improve predictive performance.

The proposed system leverages advanced machine learning and deep learning techniques, including convolutional neural networks (CNNs) for image analysis and ensemble models for structured clinical data. By combining multiple data modalities, the system captures complex relationships and patterns that are not detectable through single-source analysis. Data preprocessing techniques such as normalization, feature extraction, and dimensionality reduction are employed to enhance model efficiency and accuracy.

**Keywords:** Multi-modal stroke prediction, machine learning, deep learning, convolutional neural networks (CNN), electronic health records (EHR), medical imaging, MRI, CT scan, feature fusion, data integration, predictive analytics, healthcare analytics, risk assessment, early diagnosis, clinical decision support systems, ensemble learning, personalized medicine, biomedical data analysis, stroke prevention.



## I. INTRODUCTION

Stroke is a serious medical condition that occurs when the blood supply to the brain is disrupted, either due to blockage (ischemic stroke) or rupture (hemorrhagic stroke). It is one of the leading causes of death and long-term disability worldwide, placing a significant burden on healthcare systems and affecting the quality of life of millions of individuals. Early prediction and timely intervention are crucial in reducing the severity of stroke outcomes and improving survival rates. However, accurate prediction remains a challenging task due to the complex and multifactorial nature of the disease.

Traditional stroke prediction methods primarily rely on limited clinical parameters such as age, blood pressure, cholesterol levels, and medical history. While these factors are important, they often fail to capture the complete picture of a patient's health status. As a result, conventional models may produce lower accuracy and may not be suitable for early-stage detection or personalized risk assessment. Moreover, manual diagnosis by clinicians can be time-consuming and subject to variability, especially in resource-constrained environments.

With the advancement of artificial intelligence, machine learning, and data analytics, there is a growing opportunity to

enhance stroke prediction systems. Modern healthcare generates large volumes of diverse data, including medical imaging (MRI and CT scans), electronic health records (EHR), genetic information, and lifestyle data. Each of these data sources provides valuable insights, but when used independently, they may not fully represent the underlying risk factors. This limitation has led to the development of **multi-modal approaches**, which integrate multiple types of data to improve prediction performance.

## II. LITERATURE REVIEW

The field of stroke prediction has seen significant advancements with the integration of machine learning and deep learning techniques. Researchers have explored various approaches using clinical, imaging, and hybrid data sources to improve prediction accuracy and early diagnosis.

Several studies have focused on traditional machine learning algorithms such as Logistic Regression, Support Vector Machines (SVM), and Decision Trees for stroke prediction using structured clinical data. These methods utilize patient information such as age, hypertension, diabetes, and cholesterol levels. While these approaches provide reasonable accuracy, they often lack the capability to capture complex nonlinear relationships among features, limiting their predictive performance.



With the emergence of deep learning, researchers have started using Convolutional Neural Networks (CNNs) to analyze medical imaging data such as MRI and CT scans. These models have demonstrated high effectiveness in detecting brain abnormalities and identifying stroke lesions. However, image-based models alone may not consider patient history and lifestyle factors, which are critical for comprehensive stroke risk assessment.

Recent studies have introduced ensemble and hybrid models that combine multiple machine learning techniques to enhance prediction performance. For example, Random Forest and Gradient Boosting algorithms have been widely used due to their ability to handle high-dimensional data and reduce overfitting. These models show improved accuracy compared to single classifiers but still rely mainly on structured datasets.

A growing body of research emphasizes the importance of **multi-modal data integration** for stroke prediction. Multi-modal systems combine diverse data sources such as electronic health records (EHR), medical imaging, genetic data, and lifestyle information. Feature fusion techniques, including early fusion and late fusion strategies, have been applied to integrate heterogeneous data effectively. These approaches enable models to capture complex

interdependencies among various risk factors, leading to improved prediction accuracy and robustness.

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### III. EXISTING SYSTEM

The existing systems for stroke prediction primarily rely on traditional clinical assessment methods and basic machine learning models that use limited patient data. These systems are generally designed to analyze structured data such as patient demographics (age, gender), medical history (hypertension, diabetes, heart disease), and lifestyle factors (smoking, alcohol consumption). While these parameters provide useful insights, they often fail to capture the complete complexity of stroke risk.

In many healthcare settings, stroke prediction is still largely dependent on manual evaluation by medical professionals. Clinicians use scoring systems and risk calculators such as the Framingham Stroke Risk Profile to estimate the likelihood of stroke occurrence. Although these tools are widely used, they are based on generalized statistical models and may not provide personalized or highly accurate predictions for individual patients.

Some existing systems incorporate machine learning algorithms like Logistic Regression, Decision Trees, and Support Vector Machines (SVM) to improve prediction accuracy. These models are trained on historical clinical



datasets and can identify patterns in structured data. However, they are typically limited to single-modal data sources and do not utilize advanced data types such as medical imaging or genetic information. As a result, their predictive performance is often constrained.

In recent developments, a few systems have begun integrating medical imaging data such as MRI and CT scans using deep learning techniques like Convolutional Neural Networks (CNNs). These systems are effective in detecting stroke-related abnormalities in brain images. However, they operate independently of other critical patient data and lack a holistic view of the patient's condition.

Another limitation of existing systems is the lack of real-time prediction and decision support capabilities. Many models are designed for offline analysis and are not integrated into clinical workflows, making it difficult for healthcare providers to use them effectively in emergency or time-sensitive situations.

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#### IV. PROPOSED SYSTEM

The proposed system introduces a **multi-modal stroke prediction framework** that integrates diverse data sources to provide accurate, reliable, and early prediction of stroke risk. Unlike traditional systems that rely on a single type of data, this approach combines **medical imaging (MRI/CT scans)**,

**electronic health records (EHR), demographic details, and lifestyle factors** to create a comprehensive patient profile.

The system is designed using advanced **machine learning and deep learning techniques** to analyze both structured and unstructured data. Convolutional Neural Networks (CNNs) are utilized to extract meaningful features from medical images, enabling the detection of subtle brain abnormalities associated with stroke. At the same time, structured clinical data is processed using algorithms such as Random Forest, Gradient Boosting, and Support Vector Machines (SVM) to identify key risk factors and patterns.

A key component of the proposed system is the **multi-modal feature fusion mechanism**, where features extracted from different data sources are combined using hybrid models. This fusion can be performed using early fusion (combining raw features) or late fusion (combining model outputs), allowing the system to capture complex relationships between various risk indicators. This significantly enhances prediction accuracy and robustness compared to single-modal systems.

The system architecture includes modules for **data collection, preprocessing, feature extraction, model training, and prediction**. Data preprocessing techniques such as normalization, missing value handling, and



dimensionality reduction are applied to improve model performance.

## V. METHODOLOGY

The methodology of the proposed **multi-modal stroke prediction system** is designed to systematically integrate and analyze heterogeneous data sources for accurate and early stroke risk prediction. The overall process consists of multiple stages, including data collection, preprocessing, feature extraction, model training, multi-modal fusion, and prediction.

Initially, **data collection** is performed from various sources such as electronic health records (EHR), medical imaging datasets (MRI/CT scans), and patient lifestyle information. This ensures that both structured and unstructured data are available for comprehensive analysis. The collected data may include parameters like age, blood pressure, glucose levels, medical history, and brain scan images.

In the **data preprocessing** stage, the raw data is cleaned and transformed to make it suitable for model training. Missing values are handled using imputation techniques, and noisy or inconsistent data is removed. Structured data is normalized and encoded, while image data is resized, enhanced, and augmented to improve model generalization. This step

ensures data quality and consistency across different modalities.

Next, **feature extraction** is carried out separately for each data type. For medical images, Convolutional Neural Networks (CNNs) are used to automatically extract deep features that represent stroke-related patterns. For structured clinical data, statistical methods and machine learning techniques are applied to identify significant features influencing stroke risk. Dimensionality reduction techniques such as Principal Component Analysis (PCA) may also be used to reduce complexity.

The extracted features are then combined in the **multi-modal fusion stage**. Fusion techniques such as early fusion (feature-level integration) or late fusion (decision-level integration) are employed to merge information from different modalities. This integration allows the system to capture complex relationships between various risk factors and improves predictive performance.

Following fusion, the system proceeds to the **model training phase**, where machine learning models such as Random Forest, Gradient Boosting, or hybrid deep learning models are trained on the combined dataset. The model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score to ensure reliability and effectiveness.





In above screen user is login and after login will get below page



In above screen user can click on 'Load & Process Dataset' link to load and process both images and clinical dataset and then will get below page



In above screen in first blue two lines can see number of images loaded with different class labels and then can see loaded clinical data values and now click on 'Train Multi-Modal CNN & LSTM Models' link to train model and get below page



In above screen can see both models trained and CNN got 98% accuracy and LSTM got 81% accuracy and can see other metrics like precision, recall and FSCORE in tabular format. In graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars. Now click on 'Predict Disease' link to get below page



In above screen entering some clinical and wearable data and then uploading test image and then click on button to get below page



In above screen in blue text can see LSTM on clinical data and CNN on image data predicted



patient health as Normal and in graph x-axis represents normal and stroke disease type and y-axis represents probability and can see NORMAL got high probability. Now upload and test other image



In above screen entering some other clinical data and then uploading related image and then press button to get below page



In above screen given clinical and image data predicted as 'STROKE' and in graph also stroke got high probability so can say patient health condition is not good.

Similarly upload any other test data and image and then perform prediction.

### VIII. CONCLUSION

The **Multi-Modal Stroke Prediction System** provides an effective approach for early stroke risk identification by combining different healthcare data sources such as medical images, electronic health records, genetic

details, and lifestyle information. Unlike traditional systems that depend on limited clinical parameters, the proposed system uses machine learning and deep learning techniques to analyze multiple patient-related factors and produce more accurate predictions.

By using CNN models for MRI/CT image analysis and machine learning algorithms for clinical data processing, the system can detect hidden patterns related to stroke risk. The multi-modal fusion technique improves the reliability of prediction by combining useful features from all data sources. This helps doctors identify high-risk patients at an early stage and take preventive action before serious complications occur.

Overall, the proposed system supports accurate, fast, and personalized stroke prediction. It can be used as a clinical decision support tool in hospitals and healthcare centers. In the future, the system can be improved with larger datasets, real-time monitoring devices, explainable AI methods, and integration with hospital management systems to provide better patient care and reduce stroke-related deaths and disabilities.

### IX. FUTURE WORK: Future work for this

The proposed multi-modal stroke prediction system can be further enhanced in several



directions to improve its accuracy, scalability, and real-world applicability. One important area of future work is the integration of **real-time health monitoring data** from wearable devices such as smartwatches and fitness trackers. Continuous monitoring of parameters like heart rate, blood pressure, and physical activity can provide dynamic inputs, enabling more timely and proactive stroke risk prediction.

Another significant improvement can be achieved by incorporating **larger and more diverse datasets** from multiple hospitals and regions. This would help in improving the generalization capability of the model and reduce bias, making the system more reliable across different populations. Additionally, integrating **genomic and biomarker data** can further enhance personalized prediction and enable precision medicine approaches.

Future work can also focus on implementing **Explainable AI (XAI)** techniques to improve model transparency. Providing clear explanations for predictions will help healthcare professionals better understand the system's decisions and increase trust in clinical environments. Techniques such as feature importance visualization and attention mechanisms can be explored for this purpose.

The system can be extended by developing a **mobile or web-based application** for easy accessibility by both doctors and patients.

Integration with hospital information systems and cloud platforms will allow seamless data sharing and real-time decision support. Security and privacy mechanisms, such as encryption and secure data storage, should also be strengthened to protect sensitive patient information.

Furthermore, future enhancements may include the use of **advanced deep learning architectures** such as transformers and hybrid neural networks to improve feature extraction and prediction performance. Automated model updating and continuous learning techniques can also be implemented to adapt to new data over time.

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