

AI-Driven Stroke Prediction and Outcome Forecasting Using Neuroimaging and Clinical Stream Data

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Abstract

In the world, stroke is one of the top causes of death and permanent disability. The ability to quickly identify patients at risk for stroke is paramount in improving patient outcomes and in decreasing healthcare costs. The clinical experience of the doctor and the reading of the picture is the basis of current diagnosis methods, so there is a time delay in the diagnosis process. With the development and advancement of Artificial Intelligence (AI) in recent years, it has become possible to collect and integrate several health care information sources and offer better predictive power. The paper introduces a conceptual explainable multimodal AI framework that integrates the neuroimaging information and clinical data for early prediction of stroke risk. The framework combines structured clinical data with the deep learning features derived from the CT/MRI scans, leverages an attention mechanism for the fusion, and adds explainable AI techniques for increased transparency and trust with the clinical team. The architecture of the proposed system is different from the conventional black-box models in terms of giving emphasis to interpretability, scalability, and clinical usability. It can assist health care workers with timely diagnosis, developing individual treatment plans and better handling of patients.

Keywords— Stroke Prediction, Explainable Artificial Intelligence, Multimodal Learning, Neuroimaging, Clinical Data, Deep Learning.

1. Introduction

Stroke is a leading neurological condition and a serious condition that impacts millions of people every year. World Health Organisation (WHO) states that stroke remains a leading cause of death and permanent disability in the world. The success of treatment depends mainly on the rapid and accurate diagnosis. The failure to recognize the severity of the stroke can diminish the effectiveness of therapeutic measures.

AI has proven to be a promising technology to help physicians and healthcare workers with diagnosis. In medical image analysis, deep learning systems have shown great performance, and in the prediction from EHR, machine learning algorithms have shown good performance.

Many current approaches, however, require imaging or clinical information alone, and so have incomplete patient representation.

A current challenge with the existing AI systems is that they are not interpretable. Physicians are often reluctant to accept black box predictions without the explanation as to why. Explainable Artificial Intelligence (XAI) aims to tackle this issue by offering clear explanations for AI's decisions.

In this paper, we suggest an explainable multimodal AI architecture, which combines clinical data and neuroimaging features, into a single architecture.

2. Related Work

There have been a number of studies investigating the use of artificial intelligence in the diagnosis of stroke. Traditional machine learning techniques were mostly based on structured clinical parameters like cholesterol level, hypertension, age, diabetes, and lifestyle risk factors. These methods provided satisfactory predictive accuracy, but failed to reproduce complex anatomical abnormalities detectable in brain images.

Medical image analysis was greatly enhanced by deep learning methods via Convolutional Neural Networks (CNNs) which automated the extraction of the spatial features from the CT and MRI scan. Recently, transformer-based architectures have demonstrated improved performance in capturing the dependencies of long-range features in medical images.

The integration of heterogeneous healthcare data sources has generated a lot of interest in multimodal learning. Combining imaging information with electronic health records makes it possible to have a more full picture of the patient, which helps to increase the accuracy of predictions. But most of the current multimodal methods are still not explainable and are too complex to be used in the real clinical setting.

Table 1. The existing approaches are compared. Comparisons of existing approaches.

Approach	Imaging Data	Clinical Data	Explainability
Machine Learning	✗	✓	Limited
CNN-based Models	✓	✗	Limited
Transformer Models	✓	Partial	Moderate
Multimodal Deep Learning	✓	✓	Limited

Proposed Framework	✓	✓	✓
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3. Proposed Explainable Multimodal Framework

The suggested framework is made up of five interlinked components, which together contribute to early stroke risk evaluation.

A. Data Acquisition

The framework leverages two sources of healthcare information that complement each other:

☐ Brain CT/MRI images

Clinical data such as demographics, laboratory test results, medical history and physiological data.

B. Data Preprocessing

Imaging and clinical data are preprocessed to enhance the data quality. Neuroimaging data undergo image normalization, image resizing and removal of artifacts, whereas missing value handling, normalization, and feature encoding are applied to clinical records.

C. Feature Extraction

High-level spatial representations are derived from neuroimaging data by deep neural networks. At the same time, the structured clinical variables are converted to meaningful numerical representations by feature encoding techniques.

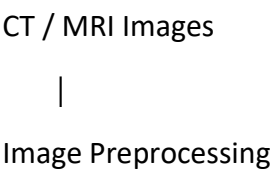
D.Multimodal Feature Fusion, D.

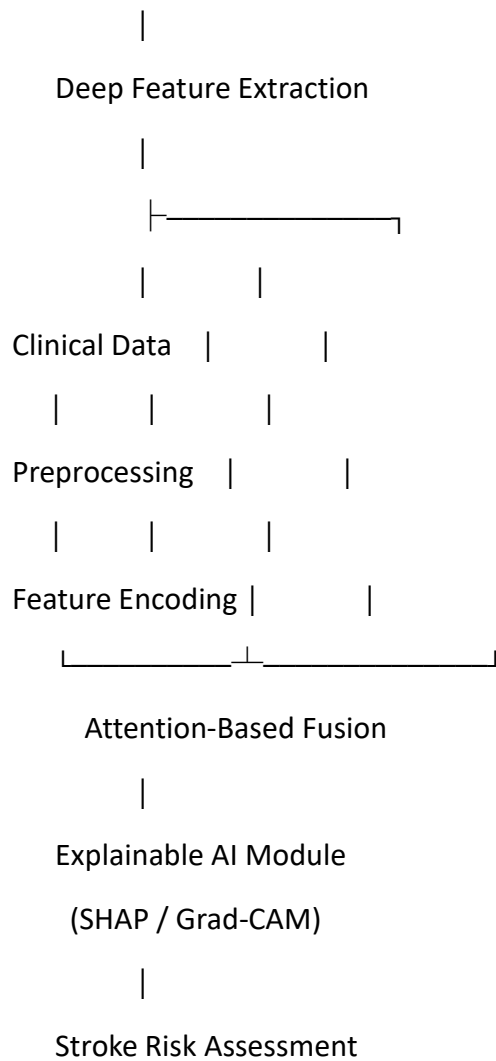
An attention-guided fusion mechanism combines extracted imaging and clinical features, giving weight to those of clinical relevance and ensuring that complementary knowledge from both modalities is maintained.

E. Explainable Decision Module

In contrast to traditional prediction systems, the proposed framework adopts explainability methods like SHAP and Grad-CAM to pinpoint significant clinical parameters and image regions that drive prediction. The explanations enhance transparency and clinician confidence in decision-making.

Figure 1. Proposed Explainable Multimodal AI Framework





Key Contributions

This work's main contributions are:

A conceptual multimodal framework integrating neuroimaging and clinical information.

The use of explainable AI techniques to enhance model transparency:

A fusion approach based on attention for comprehensive patient representation.

A clinically interpretable architecture appropriate for the future application in health care.

A scalable design flexible to various hospital settings.

4. Discussion

The proposed framework provides solutions that tackle some of the major issues related to the current stroke forecast systems. Imaging and clinical data are merged to represent complementary patterns not captured by either of the data modalities. The integration of explainable AI also enhances transparency by providing clinicians with insights into how predictions are made.

The envisioned architecture should facilitate healthcare practitioners with early risk stratification, treatment planning, and follow-up care of patients. Furthermore, explainability can boost physician trust and enable regulatory acceptance for AI-supported healthcare systems.

There are some problems yet to be addressed. The data variability from one healthcare institution to another, privacy issues, computational requirements, and hospital information system integration should be further explored. Another area of future research could be the development of federated learning and lightweight AI models in resource-limited healthcare settings.

5. Conclusion

This paper introduced a multimodal artificial intelligence model based on explainability for early stroke risk assessment by combining neuroimaging data with clinical information. The proposed conceptual architecture combines deep feature extraction, multimodal fusion, and explainable AI techniques with all in a single decision support system. The framework includes a focus on transparency and clinical interpretability, which should improve the trust of physicians and facilitate rapid diagnosis and personalized treatment planning. The future study might extend the framework to validate with multi-institutional datasets and incorporate privacy preserving learning techniques for deployment of real-world applications.

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