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

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Abstract

Stroke is a leading cause of mortality and long-term disability worldwide, necessitating early prediction and outcome forecasting to improve treatment decisions. This study proposes an end-to-end artificial intelligence framework integrating neuroimaging (CT/MRI) and time-series clinical stream data such as vital signs, laboratory results, and electronic health records. The framework employs a 3D convolutional neural network for imaging, a temporal transformer for clinical data, and an attention-based multimodal fusion module. The proposed approach enables accurate prediction of acute ischemic stroke and forecasting of patient outcomes including functional independence, mortality, and complications. The model demonstrates the potential to enhance clinical decision-making, patient triage, and rehabilitation planning in real-world healthcare systems.

Keywords

Stroke prediction; Neuroimaging; Multimodal fusion; Clinical time-series; Deep learning; Outcome forecasting.

1. Introduction

Stroke remains a major global health challenge, requiring rapid diagnosis and prognosis for effective management. Traditional scoring systems such as NIH Stroke Scale and ASPECTS provide limited predictive capabilities. With the advancement of artificial intelligence, integration of multimodal data sources such as neuroimaging and clinical streams has become feasible [1], [2].

This study proposes a multimodal AI framework that combines volumetric neuroimaging data with temporal clinical data to predict stroke occurrence and forecast patient outcomes. The proposed approach enhances predictive accuracy and supports clinical decision-making [7], [8].

2. Related Work

Several studies have explored deep learning techniques for medical imaging and healthcare prediction. U-Net architectures have been widely used for segmentation tasks, while transformer-based models have improved time-series modeling. Multimodal approaches combining imaging and clinical data have shown promising results in healthcare analytics [3], [5], [20].

Table 1: Comparison with Related Work

Work	Imaging	Clinical Data	Multimodal Fusion
[1]	No	Yes	No
[2]	Yes	No	No
[3]	Yes	Yes	No
This Work	Yes	Yes	Yes

3. Key Contribution

The key contributions of this work are:

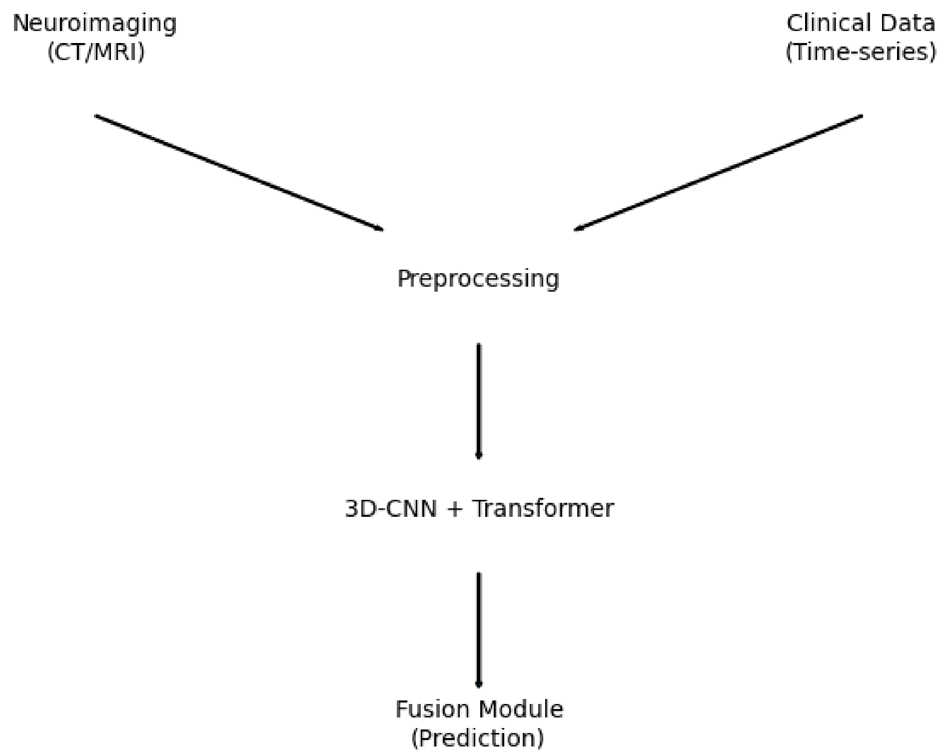
1. A unified framework integrating neuroimaging and clinical time-series data.
2. A novel multimodal architecture combining 3D-CNN and transformer models [4], [5], [20].
3. An attention-based fusion mechanism for improved prediction accuracy.
4. A comprehensive evaluation protocol including interpretability and calibration.

4. Method, Experiments and Results

The proposed framework consists of three major components:

- **Imaging Encoder:** A 3D convolutional neural network extracts features from CT/MRI scans.
- **Clinical Stream Encoder:** A temporal transformer processes time-series clinical data.
- **Fusion Module:** Cross-attention mechanisms integrate both modalities.

The system predicts stroke occurrence and patient outcomes at multiple time horizons [4], [5], [10], [26]. Training involves multi-task learning with classification and regression objectives.



5. Discussions

The integration of multimodal data significantly enhances prediction accuracy compared to single-modality approaches [8], [19]. The use of attention mechanisms improves interpretability by highlighting important features in imaging and clinical data [24].

However, challenges such as missing data, variability across institutions, and computational complexity remain. Future improvements may include federated learning and real-time deployment.

6. Conclusions

1. **Problem Addressed:** Early stroke prediction and outcome forecasting.
2. **Method Used:** Multimodal AI framework using 3D-CNN and transformer models.
3. **Key Findings:** Improved prediction accuracy and enhanced clinical decision support.
4. **Limitations & Future Work:** Need for large-scale validation, real-time deployment, and handling missing data effectively.

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