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A Comparative Deep Learning Approaches for Heart Disease Prediction

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ABSTRACT

Hypertension significantly contributes to global morbidity and mortality by increasing cardiovascular disease risks, including stroke and heart disease. Early detection is essential for intervention and improve outcomes. This study explores deep learning systems including Long Short-Term Memory, Bi- Long Short-Term Memory, Gate Recurrent Unit, and Bi-Gate Recurrent Unit to predict and classify hypertension using healthcare datasets. Data standardization, missing value treatment, and dataset balancing were done in preprocessing to increase model performance. Significant variables such as age, body mass index, glucose levels, and lifestyle factors were scrutinized. Of all the models used, Bi-GRU outperformed the others with accuracy, recall, and F1 scores of 97.62%, 97.35%, and 98.66%, respectively. Overall, the research demonstrated the efficacy of using AI to predict and prevent hypertension.

Keywords: Bi-GRU, Bi-LSTM, GRU, heart illness, hypertension, LSTM, stroke

INTRODUCTION

According to World Health Organization (2013), high blood pressure, or hypertension, is a chief worldwide health concern related with dire cardiovascular illnesses. It frequently presents no symptoms, thus making timely diagnosis of utmost importance for effective control. The WHO states that hypertension annually causes 7.5 million deaths and influences more than 1.13 billion individuals globally. Even with progress, the treatment and control rates of this condition remain dismally low. Risk factors for hypertension include Lifestyle behaviours (e.g., diet, physical inactivity). Obesity and genetic predisposition. Psychological stress and pre-existing health conditions. Machine learning and artificial intelligence approaches have

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appeared as powerful tools, for predicting and managing hypertension by analysing large datasets, identifying patterns, and enabling timely interventions. Gaps by incorporating optimization techniques within a decision-tree-based classification system.

LITERATURE REVIEW

Singh et al. (2023) suggested a hybrid model for hypertension prediction that relied on deep learning. Utilizing well-labelled and balanced data was crucial to maximise the effectiveness of a deep learning method. Consequently, researchers employed transfer learning to leverage the information from a related discipline. Kanna et al. (2023) suggested using a time series study of patients' real-time BP data to develop a vector autoregressive model for hypertension monitoring and systolic and diastolic blood pressure forecast. Designers were concerned about the imbalanced data collection, as it significantly reduced the effectiveness of the forecast model. Ji et al. (2023) discussed examination proposed a distinctive approach that integrated a learning model with rule-founded mining to offer a search tool.

Chen et al. (2022) indicated that the machine learning algorithms could create a straightforward and harmonious prediction model for hypertension by utilizing anthropometric measurements. It examined the effectiveness of 13 different prediction models that utilized anthropometric measures. Based on the results, the light GBM model outperformed the decision tree model with an area below the curve of 69% and a precision rate (AR) of 74. Chen et al. (2023)demonstrated the utility of AI-based approaches across multiple domains. Decision tree models like CART showed promise by handling diverse feature types and capturing interactions. For example, studies report accuracies of up to 84.5% using tree-based models such as XGBoost.neural network approaches, including Support Vector Machines and vector quantization, showed effective in niche populations, achieved precision levels around 88%. Althaph et al. (2024)reported hybrid models integrating deep learning with transfer learning frameworks or rule-based mining demonstrated superior performance. For instance, Bidirectional LSTM prototypes excel at capturing long-range addictions in sequential data, with AUC values exceeding 95% in some studies. These findings underscored the importance of selecting suitable models and pre-processing methods to complete high prediction accuracy.

METHODOLOGY

Data Collection and Preprocessing

The dataset, sourced from Kaggle's healthcare category, included 40,910 samples with 11 features such as age, sex, BMI, hypertension status, and glucose levels. Data preprocessing steps included:

- Handling Missing Values: Rows with missing data were dropped to ensure unbiased training.

- Standardization: Continuous variables were normalized using z-score normalization.
- Balancing the Dataset: Oversampling methods were applied to address class imbalances.
- Categorical Encoding: Features like sex and smoking status were label-encoded.

Feature Selection

The aim of this study was to identify pertienent variables for hypertension prediction. This study carried out correlation analysis to confirm that the variables involved in the model were relevant and standardized the variables so that effectively contributed to the model's accuracy. The overall process flow was illustrated in Figure 1.

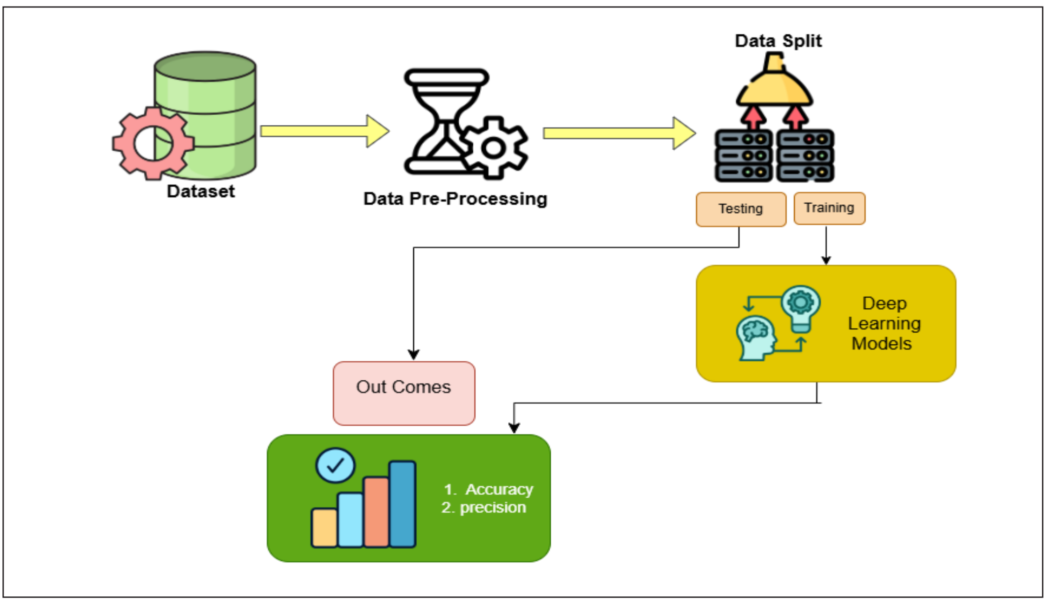

Figure 1. Design and architecture of the suggested model

Long Short-Term Memory

In healthcare, LSTMs have found wide application since their introduction in 1997, especially with temporal health data where patterns emerge (and sometimes re-emerge) over time. The structure encompassed an input layer, LSTM layers, and dense layers that served as output layers for prediction. The components included input gates that evaluated incoming data, forget gates that reset irrelevant information, and output gates that determined relevant outputs. The LSTM network's memory management capabilities make it a good candidate for forecasting intricate things like high blood pressure.

Bidirectional Long Short-Term Memory

Bidirectional LSTMs surpassed standard LSTMs in performance. They interpreted data in both forward and backward directions by utilizing two layers of LSTMs elements where one inhabits the forward direction and reads the input sequence from left to right and the other layer that predominantly served outputs from the backward direction. This second LSTM layer reads the input sequences from right to left. Thus, the two-layer LSTM served as context encoders encapsulating the forward and backward interpretations of the input sequence. Allegedly, these two layers helped the Bi-LSTM make FULL context aware predictions based solely on the observed input data.

Gated Recurrent Unit

Gated Recurrent Unit (GRU) networks offered a streamlined and efficient alternative to the more complex LSTM networks. Like LSTMs, GRUs were adept at processing sequential data, but they operated with lower computational demands. A GRU had two gating mechanisms—reset gates and update gates—that controlled the flow of information. This gating mechanism allowed the GRU a better chance of getting necessary information through as needed compared to your typical RNN. It also made the GRU about twice as fast in terms of training time.

Bidirectional Gated Recurrent Unit

Bidirectional GRU extended the functionality of regular GRUs by incorporating forward and backward processing layers. This architecture consented the prototypical to capture comprehensive dependencies within sequential data, similar to Bi-LSTMs. Bi-GRUs were particularly suited for applications requiring full contextual understanding, such as analysing health data to predict risks of hypertension.

- Hypertension Prediction: The Bi-GRU model outperformed other methods, recording an accuracy of 97.62%; a recall rate of 97.35%; and an F1 score of 98.66%.
- Stroke Prediction: Bi-LSTM obtained exceptional outcomes, achieving an accuracy of 97.66%, a recall of 97.40%, and an F1 score of 98.68%.
- Heart Disease Prediction: GRU showed the performance best, achieving accuracy of 99.48% during both train and validation phases. Accuracy and loss graphs indicate that Bi-LSTM and Bi-GRU models converged quickly to predictive hypertension and stroke.

CONCLUSION AND FUTURE WORK

The potential of deep learning models to predict hypertension and related conditions was remarkable, particularly Bi-GRU and Bi-LSTM architectures. These deep learning architectures were effective at processing sequences such as time series, which in the context of predicting medical conditionsThis approach supported proactive healthcare strategies and opened avenues for integrating real-time wearable data to improvepreventive care. Future work will explore the applicability of these models across diverse datasets and conditions, further enhancing their clinical utility.

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