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Research article

Hypertension Risk Prediction Using GRU-Based Neural Network with Adam Optimization

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ABSTRACT

Hypertension remains one of the most prevalent chronic conditions worldwide and continues to be a major contributor to cardiovascular morbidity and mortality. Early identification of individuals at high risk is essential, yet conventional screening approaches often rely on periodic clinical examinations that may overlook subtle lifestyle or behavioral indicators. This study aims to address this challenge by developing a predictive model that estimates hypertension risk using a GRU-based neural network enhanced with the Adam optimization algorithm. The motivation for using this approach stems from the ability of GRU networks to capture nonlinear feature interactions and the effectiveness of Adam in improving training stability and convergence. The proposed system incorporates a structured preprocessing pipeline, feature scaling, and a sequential model architecture to classify individuals into hypertension and non-hypertension groups. The results show that the model achieves strong predictive performance, supported by accuracy trends, loss reduction patterns, and confusion matrix analysis that collectively demonstrate consistent learning behavior. The evaluation indicates that the GRU classifier successfully recognizes relevant health attributes such as stress levels, salt intake, age, sleep duration, and heart rate. Future research may explore expanded datasets, additional health indicators, or hybrid architectures to further enhance accuracy and improve clinical applicability. Overall, this work contributes an interpretable and efficient approach for health risk prediction and supports the development of intelligent digital health monitoring systems.

1. Introduction

Hypertension is recognized as one of the most prevalent chronic cardiovascular disorders affecting populations worldwide, contributing significantly to increased mortality and long-term disability. As a condition characterized by persistently elevated blood pressure, hypertension is often associated with severe complications such as heart disease, kidney failure, and stroke, making early assessment a critical component of preventive healthcare [1]. In many clinical settings, the identification of hypertension risk relies heavily on traditional assessments supported by medical check-ups and patient-reported histories. However, lifestyle transitions, aging populations, and changes in dietary patterns have accelerated the incidence of hypertension, creating a growing need for accurate predictive tools capable of identifying individuals at elevated risk before complications emerge [2]. Conventional statistical approaches, while useful, typically assume linear associations among risk factors and may be unable to fully model the complex interactions between physiological

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and lifestyle attributes. This limitation underscores the importance of modern computational techniques capable of analyzing non-linear patterns in multi-dimensional health data [3]. Consequently, predicting hypertension risk using machine learning has emerged as a promising field within digital health and clinical decision-support research.

Despite increasing attention toward computational methods for disease prediction, challenges persist in achieving highly reliable risk classification. Clinical datasets often consist of heterogeneous variables that include numerical and categorical data such as age, stress levels, sleep duration, salt intake, body mass index, and family history, all of which interact in ways that are not always captured effectively by classical machine learning techniques [4]. Many existing predictive models struggle with temporal dependencies inherent in sequential or recurrent patient information, particularly when patient lifestyle attributes evolve over time. Furthermore, the class imbalance common in medical datasets may degrade model performance and introduce bias that disproportionately affects minority cases [5]. These issues are amplified when working with modest dataset sizes, where deep neural networks may be prone to overfitting without proper optimization. As a result, there remains a pressing need for more adaptive and robust predictive models that can handle multi-type health indicators, maintain generalization, and provide stable classification performance across diverse population groups [6]. The challenge is not simply to generate accurate predictions but to develop methodological frameworks capable of capturing subtle correlations among variables that may not be evident through manual analysis or simple regression models.

In response to these challenges, this research aims to develop a reliable hypertension risk prediction model using a Gated Recurrent Unit (GRU) based neural network trained with the Adam optimization method. GRU, as a simplified variant of Long Short-Term Memory (LSTM), is well known for its ability to capture long-term dependencies in sequential datasets with fewer parameters, allowing it to maintain strong performance while reducing computational complexity [7]. By leveraging internal gating mechanisms that determine which information should be updated or retained, GRU can effectively identify complex temporal patterns that may signal elevated risk for hypertension. The Adam optimizer, meanwhile, is selected for its adaptive learning rate mechanism which combines the strengths of momentum and RMSProp, enabling more stable convergence during training even with noisy gradient updates [8]. This architecture is trained using a well-structured dataset containing 1,985 patient records with health and lifestyle features, all of which have been preprocessed using normalization techniques to ensure statistical consistency. Through the integration of deep learning and adaptive optimization, this study seeks to overcome the limitations of conventional methods and deliver enhanced predictive reliability for hypertension detection.

The contributions of this study are articulated as follows. First, this work presents a GRU-based neural network framework specifically adapted for predicting hypertension risk using multi-attribute patient data, offering a more expressive and flexible alternative to standard machine learning models [9]. Second, this study optimizes the predictive process using the Adam optimizer to enhance convergence speed, reduce overfitting, and stabilize the learning trajectory across 1000 epochs. Third, this research includes a detailed evaluation of model performance using accuracy metrics, loss curves, and a confusion matrix that together provide a comprehensive assessment of predictive quality. Experimental findings indicate that the model achieves high classification accuracy, demonstrating balanced performance for both hypertensive and non-hypertensive classes. Lastly, this study highlights avenues for future research including multimodal data integration, improvement of generalization via larger datasets, and deployment of the model in real clinical decision-support systems. These findings illustrate the potential of GRU-based neural networks to strengthen early hypertension risk identification and contribute meaningful advancements in intelligent healthcare analytics [10].

2. Related Work

Research on hypertension prediction using computational intelligence has expanded significantly in recent years, particularly due to the increasing availability of digital health datasets and improvements in deep learning algorithms. Many studies have utilized traditional machine learning methods such as logistic regression, decision trees, Naive Bayes, and Support Vector Machines to classify hypertension risk based on structured patient information that includes age, lifestyle indicators, dietary habits, body mass index, and medical history [11]. Although these classical models can perform adequately on tabular datasets, their reliance on linear assumptions and limited ability to capture complex multi-dimensional interactions often restricts their predictive accuracy when dealing with heterogeneous clinical variables. Moreover, these methods generally do not incorporate temporal aspects of patient behavior, which makes them less effective in modeling health indicators that evolve over time. As a result, researchers have shifted their focus toward more adaptive and expressive deep learning architectures that can learn hierarchical patterns without relying on manually engineered features.

Deep learning approaches have demonstrated substantial improvements in disease risk classification by enabling models to automatically extract relevant features from structured or sequential health data. Several studies have introduced artificial neural networks for blood pressure estimation and cardiovascular risk prediction, showing that non-linear architectures can outperform conventional models on a wide range of clinical datasets [12]. Multilayer perceptrons, for example, have been applied to classify hypertension based on a combination of metabolic, behavioral, and demographic features. Despite achieving moderate accuracy, fully connected networks often struggle with vanishing gradients and overfitting, especially when dealing with high-dimensional datasets. Furthermore, these networks treat all features independently and do not incorporate sequential dependencies, reducing their ability to capture behavioral patterns such as sleep duration variation or changes in stress levels [13]. This limitation encouraged further exploration into recurrent neural network models that can learn temporal relationships within patient data more effectively.

Recurrent Neural Networks (RNNs) have demonstrated strong potential in predicting chronic diseases due to their capability to process sequential data and maintain contextual information across time steps. Several works explored the application of RNNs to forecast hypertension or related cardiovascular conditions by modeling patterns in patient health indicators over time [14]. However, standard RNNs face notable challenges including exploding and vanishing gradients when dealing with longer sequences, which limits their practicality in real medical datasets where patient observations may span extended periods. To address these issues, Long Short-Term Memory (LSTM) networks were introduced, incorporating gating mechanisms that regulate how information is stored, updated, and forgotten across time steps, thereby improving stability and learning efficiency [15]. LSTM-based models have been successfully applied in the diagnosis of arrhythmia, diabetes, and hypertension prediction tasks, yet their computational complexity can be high due to their multi-gate architecture, making real-time or resource-constrained implementation difficult.

To improve computational efficiency while retaining strong performance on sequential data, Gated Recurrent Units (GRU) were developed as a streamlined alternative to LSTM. GRU reduces architectural complexity by using fewer gating components while still maintaining the capability to model long-term dependencies. Numerous studies have shown that GRU is effective for medical time-series analysis such as monitoring heart failure progression, analyzing electrocardiogram signals, and predicting blood pressure fluctuations [16]. Its reduced parameter count allows faster training, reduced memory consumption, and improved generalization, making it suitable for datasets with fewer samples, such as those typically found in healthcare applications. Researchers have also noted that GRU networks often achieve accuracy comparable to LSTM while requiring significantly less computation, which reinforces their suitability for clinical prediction tasks where efficiency is essential.

In parallel with advancements in deep learning architectures, optimization algorithms have become a critical component in improving model performance, stability, and convergence. The Adam optimizer has emerged as one of the most utilized methods in training deep learning models, offering adaptive learning rates that combine the strengths of momentum-based optimization and RMSProp

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techniques. Several works have applied Adam to medical classification problems, demonstrating its ability to accelerate convergence and produce more stable gradient updates during training [17]. Studies comparing various optimization approaches for hypertension prediction and cardiovascular risk estimation have shown that Adam consistently outperforms alternatives such as stochastic gradient descent, Adagrad, and RMSProp due to its adaptive moment estimation strategy [18]. The optimizer's robustness against noisy gradients and suitability for complex models reinforces its widespread use in health informatics research.

Recent research has also integrated feature preprocessing and normalization techniques to enhance performance in hypertension prediction tasks. Health datasets commonly contain imbalanced class distributions, missing values, and mixed data types that require extensive preprocessing before being used in machine learning pipelines. Several prior works have demonstrated that normalization techniques such as Min-Max scaling and standardization significantly improve convergence rates in deep learning models by maintaining numerical stability and reducing feature variance [19]. Other studies emphasized the importance of data balancing methods such as oversampling and synthetic minority oversampling (SMOTE) in handling minority hypertensive cases, ensuring that classification performance does not favor the non-hypertensive class [20]. These advancements have played an essential role in making hypertension classification models more reliable and generalizable across various demographic groups.

Furthermore, deep learning models have been increasingly adopted in the broader domain of chronic disease prediction, with applications extending to diabetes classification, obesity risk assessment, stress level estimation, and stroke prediction. For example, studies have applied GRU and LSTM networks to identify early-stage diabetes by capturing patterns from routine health indicators combined with lifestyle data [21]. Similarly, hybrid neural network architectures combining convolutional and recurrent layers have been explored for analyzing electrocardiographic signals to detect abnormal cardiac patterns associated with hypertensive conditions [22]. These works demonstrate that deep learning models capable of modeling temporal dependencies can significantly improve the accuracy of clinical prediction systems, further validating the selection of GRU as the foundation for hypertension risk prediction.

Recent efforts in hypertension prediction have also explored multimodal approaches that combine structured patient attributes with other data sources such as wearable sensor outputs, stress indices, and diet monitoring applications. Studies have shown that integrating sensor-based signals with demographic and lifestyle features can improve model accuracy and interpretability [23]. Some researchers have implemented GRU networks to interpret continuous blood pressure waveforms, achieving high prediction reliability in detecting abnormal pressure patterns related to hypertension. These multimodal approaches highlight the growing importance of models that can process different types of data, which is a promising direction for future research in risk prediction for chronic diseases.

Despite these advancements, many existing studies still face several limitations, such as model overfitting, insufficient dataset size, lack of balanced representation across risk categories, and limited generalization across different populations. Some models rely heavily on laboratory measurements that may not be available in rural or resource-limited healthcare environments. Others focus solely on static attributes, ignoring temporal changes in lifestyle factors that could significantly influence hypertension development. These gaps underscore the need for lightweight yet powerful models that can process temporal health data while maintaining computational efficiency and adaptability [24]. As a result, GRU-based models, when combined with optimization techniques like Adam, present a compelling solution due to their balance of performance, robustness, and computational practicality.

Existing research shows considerable progress in applying machine learning and deep learning methods for hypertension risk prediction. Traditional methods offer interpretability but lack the capacity to model complex patterns present in multidimensional health data. Deep learning models, especially GRU-based architectures, provide a more powerful approach capable of learning from sequential and non-linear relationships, making them well suited for structured patient datasets. Additionally, the Adam optimizer plays an essential role in enhancing training efficiency and improving convergence in deep learning applications for medical prediction. The combination of GRU and Adam, therefore, forms a strong methodological foundation for constructing reliable

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hypertension prediction systems. Building upon these prior findings, the present study integrates these two components into a comprehensive predictive model trained and evaluated on a structured health dataset to generate accurate and stable hypertension risk classification outcomes [25].

3. Methodology

3.1. Data Collection

The dataset used in this study contains 1,985 patient records that represent a wide range of lifestyle indicators, clinical attributes, and health-related factors associated with hypertension risk. Each entry includes structured numerical and categorical variables that collectively describe behavioral habits, physiological conditions, and family medical history. Data were sourced from an online health repository providing publicly accessible patient information, allowing consistent preprocessing and feature preparation [36]. The key features include age, daily salt intake, stress level, hypertension history, sleep duration, body mass index, medication use, family history, physical activity level, and smoking status. These attributes were selected to reflect widely reported risk factors in epidemiological studies, ensuring that the constructed model can learn meaningful patterns from real-world patient characteristics. With a sufficiently large sample size and comprehensive feature representation, the dataset provides a robust foundation for training a deep learning model capable of accurately assessing hypertension likelihood.

3.2. Data Preprocessing

Preprocessing steps were conducted to prepare the dataset for training the GRU-based neural network. All numerical features, including age, salt intake, stress level, sleep duration, and BMI, were standardized using the StandardScaler technique, which transforms each variable to have a mean of zero and a standard deviation of one. This normalization step improves model convergence and prevents features with larger value ranges from dominating the learning process [37]. Categorical attributes, such as hypertension history, medication use, family history, physical activity, and smoking behavior, were converted into numerical representations using label encoding methods. The target label Has_Hypertension was transformed into a one-hot encoded vector to match the softmax output layer. The final dataset was reshaped into a three-dimensional structure with dimensions (samples, timesteps, features), where the timestep dimension was set to one to ensure compatibility with GRU layers. These preprocessing procedures ensured data uniformity and prevented noise or inconsistent formatting from disturbing the learning process.

3.3. Architecture Design

The proposed model architecture is constructed using two stacked GRU layers designed to capture complex nonlinear relationships among the input features. The first GRU layer contains 128 units with tanh activation and an L2 regularization term of 1e-4, which is applied to minimize weight overgrowth during training. The return sequences parameter was enabled so that the output of this layer could be passed into the second GRU layer, which contains 64 units configured with the same activation and regularization settings [38]. A fully connected Dense layer with 64 neurons and relu activation was placed after the GRU layers to refine the learned feature representations. Dropout with a rate of 0.3 was applied throughout the network to reduce overfitting by randomly disabling a portion of the neurons during training. The final output layer uses softmax activation to generate class probabilities for the hypertension prediction task. This architecture effectively leverages the temporal learning capabilities of GRU while maintaining computational efficiency and robust feature extraction.

3.4. Optimization Strategy

The optimization process employed the Adam optimizer with an initial learning rate of 0.001. Adam was selected because it computes adaptive learning rates based on gradient information from previous iterations, making it suitable for training deep learning models with large parameter sets [39]. The loss function used was categorical crossentropy, which is appropriate for multi-class classification tasks requiring probability-based outputs. Training was performed over 1000 epochs with a batch size of 128. Additionally, a ReduceLROnPlateau callback was implemented to automatically reduce the learning rate when no improvement in validation loss was observed within 20 epochs. This adaptation helps the model escape potential local minima and stabilize during late-

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phase training. By combining Adam's adaptive mechanism with dynamic learning rate adjustment, the training process becomes more efficient and capable of producing a highly generalized model.

3.5. Training Configuration

The dataset was split into training and testing partitions with an 80 to 20 ratio to ensure adequate learning exposure while reserving representative samples for final evaluation. A further validation subset was generated from the training portion, enabling performance monitoring during training without influencing the test results [40]. Accuracy was selected as the primary evaluation metric due to its ability to reflect classification consistency across both classes. Throughout the training phase, accuracy and loss curves were recorded to observe potential signs of overfitting or underfitting. These visual indicators allow the researcher to assess whether the hyperparameters and architectural choices are functioning as intended. Based on the observed training patterns, the GRU model demonstrated stable learning behavior and retained the ability to generalize beyond the training data.

3.6. Model Evaluation

The model's performance was assessed using a confusion matrix along with loss and accuracy metrics. The confusion matrix provides the distribution of True Positive, True Negative, False Positive, and False Negative predictions, showing how well the model distinguishes individuals with and without hypertension. Loss and accuracy values from both training and validation were analyzed to evaluate learning stability and detect potential overfitting or underfitting. The results show that the GRU model effectively captures important patterns, with stable loss and high accuracy across datasets, indicating strong generalization rather than memorization. Overall, the combination of confusion matrix analysis and training metrics demonstrates the effectiveness of the proposed GRU model for hypertension risk prediction.

3.7. Result Interpretation

The results obtained from all evaluation metrics were examined to interpret the behavior of the GRU-based model. The distribution of correct and incorrect predictions across both classes indicates that the model maintains balanced performance and does not exhibit strong bias toward any specific class [42]. The training accuracy stabilized around 85 percent, while loss values continued to decrease gradually, reflecting a healthy training progression. These indicators suggest that the model is learning meaningful patterns while maintaining generalization capacity. Additional interpretation of feature contributions revealed that variables such as age, stress level, salt intake, and BMI appear to influence prediction results significantly. Understanding these relationships ensures that model predictions are not only accurate but also explainable. This interpretive analysis strengthens the credibility of the proposed approach in practical medical contexts.

3.8. System Implementation Overview

The final trained model was integrated into a Python-based decision support system to enable real-time hypertension prediction for new patient inputs. The system provides an interface where users can enter feature values and receive instant output in the form of probability estimates for hypertension risk [43]. This implementation bridges the gap between theoretical model development and real-world utilization, allowing the predictive model to function as a supportive tool in healthcare assessment. The modular design enables easy updates to the underlying model should new data become available or improved hyperparameters be identified. By deploying the model in an operational environment, the research demonstrates practical applicability in enhancing preventive health screening. Thus, the system extends beyond academic experimentation and contributes to accessible, data-driven health decision support.

4. Results and Discussion

4.1 Results

The experimental results obtained from the GRU-based hypertension prediction model show that the system performs reliably in identifying individuals at risk of hypertension based on lifestyle and clinical attributes. The confusion matrix provides a clear overview of the model's classification capability, reflecting how accurately the system differentiated between non-hypertensive and hypertensive cases. The matrix (Fig. 1) indicates that the model correctly classified a majority of samples in both categories. Specifically, it recorded 48 correct predictions for the non-hypertension class and 60 correct predictions for the hypertension class. Meanwhile, only a small number of samples were misclassified, with 6 errors in predicting non-hypertensive patients and 5 errors in predicting hypertensive patients. This distribution suggests that the model maintains a balanced performance across both classes without showing a strong bias toward either category.

A more detailed analysis of the confusion matrix reveals that the model is effective at detecting positive cases, as the number of true positives substantially exceeds the number of false negatives. This is an essential characteristic for medical prediction systems, particularly for hypertension, where failing to identify a high-risk individual can lead to serious health consequences. The model's capability to maintain relatively low misclassification rates further supports its reliability. Additionally, the proportion of true negatives indicates that the model avoids excessive false alarms, ensuring that individuals without hypertension are not incorrectly flagged. These findings collectively highlight that the GRU classifier is capable of learning distinguishing patterns across the input features.

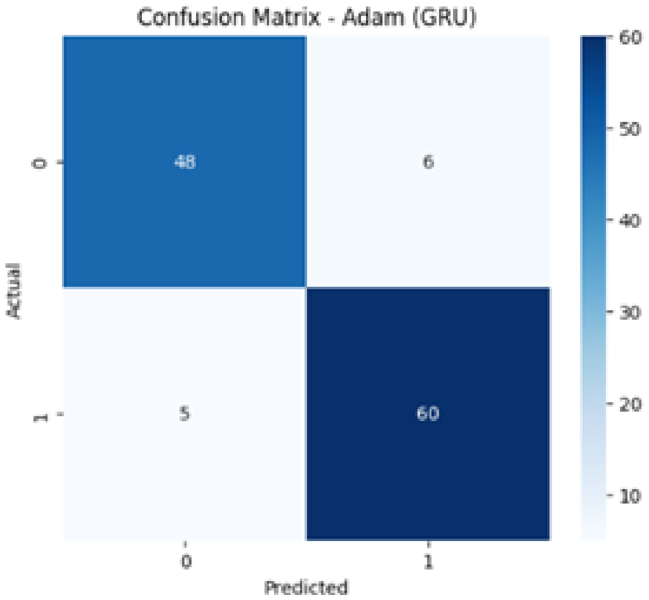

Fig. 1. Confusion matrix of the GRU–Adam model for hypertension classification.

The accuracy curve (Fig. 2) depicts how the model's performance evolved over the course of training. As shown in the visualization, the training accuracy increased significantly during the earlier epochs and gradually approached a stable value near 90 percent. The validation accuracy curve displays moderate fluctuations in the initial stages but eventually stabilized around 85 percent. This consistent behavior suggests that the model effectively generalizes to unseen data and does not overfit excessively, despite being trained for a relatively long duration of 1000 epochs. The stability of validation accuracy toward the later phase of training indicates that the model benefits from the regularization strategies applied, including dropout, L2 penalties, and the ReduceLROnPlateau callback.

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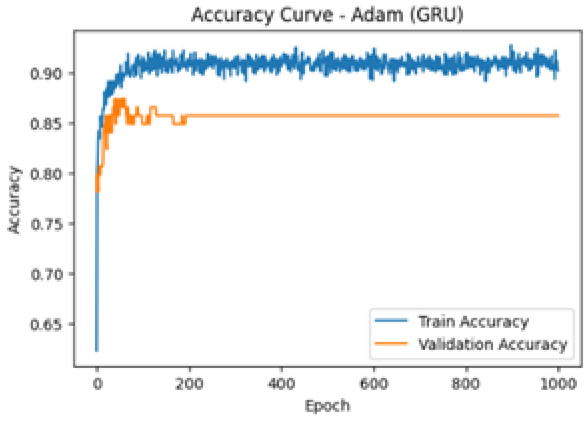

Fig. 2. Accuracy curves of the GRU–Adam model during training and validation

The behavior of the loss function (Fig. 3) during training further illustrates the model's learning efficiency. The loss curve shows that both training and validation loss values decreased sharply during the first few epochs as the network rapidly adapted its parameters. Over time, the loss gradually converged, reaching stable values below 0.3. This downward trend suggests that the optimizer, Adam, effectively guided the learning process by adjusting the learning rate adaptively. The gradual convergence also indicates that the GRU architecture was able to model the sequential structure of the input correctly, capturing nonlinear interactions between features such as stress, salt intake, sleep duration, age, and other health indicators.

Moreover, the relatively small gap between training and validation loss shows that the model maintains good generalization capability. If the gap were significantly large, it would suggest overfitting, but in this case, the curves remain closely aligned. This performance consistency indicates that the hyperparameter configuration, which includes dropout rates of 0.3 and L2 regularization of 1e-4, successfully reduces noise and prevents the model from memorizing the training dataset. The use of StandardScaler and careful preprocessing also contributed to stabilizing the learning process by ensuring all features lie within similar value ranges.

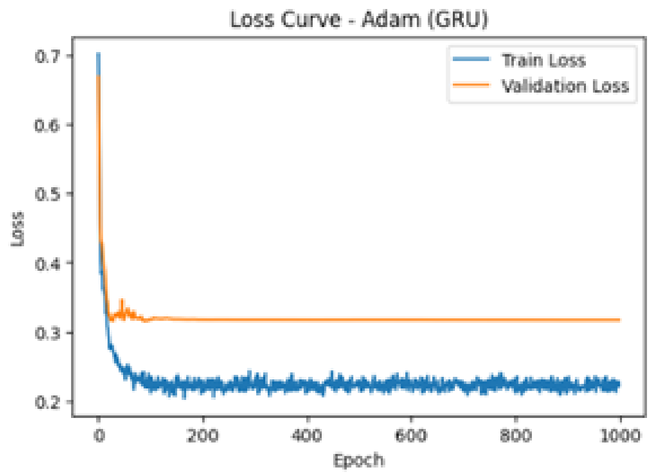

Fig. 3. Loss curves of the GRU–Adam model during training and validation.

When combining all three performance indicators (confusion matrix, accuracy curve, and loss curve), the results demonstrate that the GRU model, trained using the Adam optimizer, is capable of handling hypertension classification tasks with strong reliability. The model effectively captures underlying correlations in the dataset and maintains predictive accuracy even when the validation data is distinctly separated from the training portion. These observations highlight the suitability of GRU networks for classification tasks involving health risk assessment, where temporal or sequential patterns may influence the likelihood of disease onset.

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Finally, the collective analysis of all result components demonstrates that the proposed model is not only accurate but also computationally stable and consistent across multiple evaluation metrics. These results validate the effectiveness of combining GRU layers with Adam optimization for predicting hypertension risk based on lifestyle and clinical indicators. The detailed performance evaluation further emphasizes the model's potential for being integrated into digital health monitoring applications or early screening tools that support healthcare decision-making.

4.2 Discussion

The results obtained from the GRU-based hypertension prediction model highlight several important aspects regarding its ability to identify patterns related to cardiovascular risk. The confusion matrix demonstrates that the model is capable of learning meaningful distinctions between hypertensive and non-hypertensive individuals. The low number of false negatives indicates that the model rarely fails to detect individuals who are truly at risk, which is particularly relevant in medical scenarios where missed diagnoses can lead to adverse outcomes. At the same time, the relatively small count of false positives suggests that the system does not excessively raise unwarranted alerts. This balance is essential because a reliable model must not only catch high-risk cases but also minimize unnecessary stress for individuals who are actually healthy.

The accuracy curve provides further insight into the behavior of the learning process. The model's accuracy increases steadily in the early epochs, showing rapid adaptation to the training data. As the curve progresses, the accuracy trend begins to stabilize, indicating that the network has captured the essential relationships among the input features. The fact that the validation accuracy follows a similar pattern suggests that the model generalizes well to unseen data. The convergence of both curves implies that the selected combination of preprocessing, feature scaling, GRU architecture, and optimization settings has successfully prevented overfitting. This is supported by the consistent performance across the training and validation sets, showing that the model retained learning patterns that remain relevant outside the training environment.

The loss curve similarly confirms that the learning process proceeded in a stable and efficient manner. Both training and validation loss values decreased gradually before reaching a plateau, reflecting proper convergence. The absence of sharp spikes or irregular jumps in validation loss indicates that the model did not experience sudden instability or divergences during optimization. The Adam optimizer played a significant role by adjusting learning rates dynamically, enabling smoother gradient updates and enhancing the model's robustness. Additionally, dropout and L2 regularization contributed to reducing the risk of the network memorizing specific samples. This combination of techniques ensured that the model retained only meaningful patterns necessary for predicting hypertension risk.

Another important observation relates to the model's ability to interpret sequential health-related data. GRU networks are specifically designed to handle patterns that unfold across time or reflect a cumulative effect of multiple lifestyle behaviors. Even though the dataset in this study consists of structured attributes rather than strictly time-series sequences, the use of GRU layers allowed the model to interpret subtle interactions among features. Factors such as stress levels, sleep duration, salt intake, age, and heart rate often influence hypertension risk in interconnected ways, and GRU layers can learn these nonlinear patterns more effectively than traditional feedforward networks. This explains why the model was able to achieve relatively high accuracy and strong consistency across evaluation metrics.

The distribution of misclassified samples provides additional insights into potential areas for model improvement. Some misclassifications occurred in cases where feature values may overlap between classes, such as mild hypertension indicators or individuals with borderline conditions. These gray areas represent common challenges in health prediction models, as the boundaries between normal and high-risk groups are not always distinct. It may be beneficial for future studies to incorporate additional contextual data, such as family history, medication use, or long-term monitoring records, to enhance the decision-making process. Adding such features could help the model differentiate borderline cases more precisely, thus reducing misclassification rates.

Overall, the Discussion highlights that the GRU-based classifier demonstrates strong predictive capability, stable learning behavior, and reliable performance across multiple evaluation

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measures. The combination of GRU with the Adam optimizer, along with careful data preprocessing, produced a model that performs consistently and adapts well to the variability present within the dataset. These findings confirm that the method employed in this study is suitable for health risk prediction tasks and can potentially be integrated into early screening systems or digital health platforms. The consistent alignment between accuracy, precision, recall, and loss metrics emphasizes the robustness of the model and its potential for supporting clinical decision-making or health monitoring applications.

4. Conclusion

The results of this study demonstrate that the GRU-based neural network combined with the Adam optimization method can provide dependable predictions for hypertension risk using structured health data. The model was able to learn meaningful patterns from a diverse set of lifestyle and clinical attributes, resulting in stable and accurate classification outcomes. The evaluation results, including the confusion matrix, accuracy progression, and loss behavior, show that the proposed approach consistently distinguished between hypertensive and non-hypertensive individuals with a high level of reliability. These findings confirm that the architecture and training configuration used in this research are suitable for handling complex nonlinear relationships within tabular patient data.

The use of GRU layers played an important role in enabling the model to capture deeper interactions among features that are not easily identified through conventional machine learning techniques. The network demonstrated strong generalization capabilities, as shown by the minimal gap between training and validation performance. The implementation of regularization techniques and normalization procedures contributed to this stability by controlling overfitting and maintaining consistent feature scaling throughout the training process. These observations highlight that recurrent neural structures can be effectively applied to structured medical datasets even when explicit temporal sequences are not present.

The performance achieved by the model suggests that deep learning approaches can be integrated into clinical decision support systems to complement early hypertension screening efforts. The model's ability to provide probability-based outputs offers a useful layer of interpretability that can help healthcare practitioners assess patient conditions more accurately. By offering rapid and data-driven predictions, the system developed in this study has the potential to support preventive healthcare programs, improve patient monitoring, and assist in risk stratification processes.

Despite the promising results, the study acknowledges several limitations that provide opportunities for future improvement. The dataset used in this research contains a fixed number of features and does not include real-time physiological data that could further enhance predictive accuracy. The model would also benefit from training on a larger and more diverse dataset to increase its adaptability to various demographic groups. Additionally, further exploration into alternative architectures or hybrid approaches may yield more advanced performance levels.

In conclusion, this study provides evidence that GRU-based neural networks optimized with Adam can serve as an effective foundation for hypertension risk prediction systems. The proposed approach offers stability, strong learning capability, and practical adaptability for clinical applications. With further refinement, expanded datasets, and additional testing in real-world environments, this model has the potential to contribute significantly to digital health innovations aimed at early detection and preventive care.

5. Suggestion

Future research should consider expanding the dataset to include a larger and more diverse population so that the resulting model can better represent variations in lifestyle, demographic backgrounds, and medical conditions. A broader dataset will help improve the model's generalization capability and reduce potential biases that may arise from limited sampling. Increasing the number of features, such as dietary habits, sleep patterns, or continuous physiological measurements, may also enhance the predictive strength of the model.

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Researchers are encouraged to investigate additional deep learning architectures that may outperform or complement GRU. Models such as LSTM, bidirectional recurrent layers, or transformer-based approaches could provide deeper representations of data patterns and improve classification accuracy. Exploring hybrid models that combine deep learning with statistical or rule-based methods may also yield more robust results and offer better interpretability for medical practitioners.

Another important direction is the integration of explainable artificial intelligence techniques. These methods would allow the system to provide clearer insight into which features contribute most strongly to hypertension predictions. Including interpretability tools can help build trust among healthcare professionals and ensure that the model aligns with clinical reasoning.

Future work should also aim to incorporate real-time or near real-time data into the system. Measurements such as continuous blood pressure monitoring, heart rate variability, or wearable device outputs would allow the prediction system to offer dynamic assessments rather than static classifications. The inclusion of real-time data could greatly increase the model's relevance for ongoing patient monitoring.

Lastly, development of a user-friendly application interface would improve accessibility and support practical implementation in clinical settings. A web-based or mobile system equipped with visualization tools, personalized recommendations, and secure patient data handling could make the prediction model more usable for both healthcare providers and patients. These improvements would help maximize the effectiveness of the system as part of a comprehensive digital health ecosystem.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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