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Continuous Blood Pressure Prediction: A Time Series Approach for Enhancing Cardiovascular Health Monitoring

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Abstract: Blood pressure prediction is a critical task in healthcare, enabling proactive monitoring and intervention to prevent cardiovascular complications. In this paper, we introduce a cutting-edge hybrid model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for accurate blood pressure prediction using time-series data. The CNN component is leveraged for feature extraction and capturing spatial dependencies, while the LSTM component excels in learning temporal patterns and long-range dependencies in sequential data. Our experimental results demonstrate that the CNN-LSTM hybrid model outperforms the standalone CNN and LSTM models in terms of both accuracy and error metrics. Specifically, the hybrid model achieved an R^2 score of 0.9197, surpassing those of the CNN ($R^2 = 0.8965$) and LSTM ($R^2 = 0.9125$) models. The hybrid model also exhibited a lower Mean Squared Error (MSE) of 0.0042 and Root Mean Squared Error (RMSE) of 0.0649 compared to the CNN (MSE = 0.0053, RMSE = 0.0727) and LSTM (MSE = 0.0045, RMSE = 0.0672) models. These results underscore the performance of the CNN-LSTM hybrid model for predicting blood pressure from time-series data, offering a promising solution for improving predictive accuracy in healthcare applications. The proposed model has the capability to enhance continuous monitoring systems, ultimately contributing to better patient outcomes through timely intervention.

Keywords: *Convolutional Neural Networks (CNNs), CNN-LSTM Hybrid Model, Long Short-Term Memory (LSTM), Predictive Modeling, Temporal Pattern Recognition, , Time Series Data.*

1. Introduction

Blood pressure (BP), a critical physiological indicator of cardiovascular health, has become a significant public health challenge both globally and in the United States [1], [2]. Projections indicate that by 2030, approximately 41.4% of U.S. adults will suffer from hypertension, representing an 8.4% increase from the 2012 estimates. Consequently, 43.9% of the U.S. population is expected to be affected by various manifestations of cardiovascular disease by 2030. The economic impact of this growing burden is of equal concern, with the cost of managing hypertension alone projected to escalate to $274 billion by 2030 [3], [4].

Accurate prediction of blood pressure plays a vital role in preventing and managing hypertension-related conditions, as timely and precise monitoring can help reduce the risks associated with cardiovascular diseases [5], [6]. However, traditional blood pressure monitoring methods often rely on intermittent measurements, which may not capture dynamic variations in blood pressure over time. To address this challenge, leveraging time-series data for continuous blood pressure prediction is a promising approach to enhance patient care and outcomes[7], [8], [9].

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Traditional time-series models, such as ARIMA, have been widely utilized in disease progression studies, and are known for their ability to manage seasonal patterns and non-stationary trends. However, it struggles with noisy and sparse datasets that are often encountered in health-related studies, particularly those focusing on cardiovascular diseases. Moreover, ARIMA's reliance on manual parameter tuning can hinder its performance, particularly in dynamic environments, such as cardiovascular interventions, where quick and precise adjustments are crucial [10].

With advancements in machine learning, more sophisticated techniques have been developed to improve the prediction accuracy. These methods have the potential to transform sequences of clinical measurements into valuable insights for characterizing disease risk and progression, offering greater flexibility than traditional statistical models by better accounting for nonlinearities and interaction effects in predictors [11], [12], [13]. For example, Decision Trees (DT), Support Vector Machines (SVMs), and Random Forests (RFs) have been utilized to predict blood pressure by analyzing features extracted from time-series data. Although these models offer better performance than traditional methods, they still face challenges in managing the high dimensionality and temporal complexity of blood pressure data [14],[15],[16].

Koshimizu et al. [17] introduced a deep learning model to predict blood pressure variability, leveraging time series data and medical examination records. This multi-input, multi-output deep neural network demonstrated moderate prediction accuracy, with root mean square errors (RMSEs) ranging from 5.04 to 6.65 mmHg. A notable strength of the model is its ability to manage participants with high variability in blood pressure, making it particularly useful for patients with erratic blood pressure patterns. However, the study did not include comparisons with other models, making it challenging to thoroughly assess the novelty and effectiveness of the approach [18], [19].

Among the various techniques used for blood pressure prediction, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have become prominent because of their capability to handle complex data patterns. CNNs are particularly effective at extracting spatial features, whereas LSTMs excel at modeling temporal sequences and long-range dependencies [20], [21]. Despite their strengths, the standalone application of these models may not fully capture the intricate relationships inherent in physiological signals such as blood pressure[22], [23]. Therefore, hybrid models that combine the strengths of CNNs and LSTMs have emerged as promising solutions for more accurate and robust predictions.To overcome the limitations of individual models, hybrid architectures that combine the strengths of different neural networks have emerged as a powerful solution. In this study, we propose a CNN-LSTM hybrid model for blood pressure prediction using time series data. The CNN component effectively extracts spatial features, while the LSTM component captures temporal dynamics, leading to more accurate predictions.Our research demonstrates that this hybrid approach outperforms both the standalone CNN and LSTM models in key performance metrics, including R^2, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). By integrating CNN and LSTM architectures, the proposed model captures both the spatial and temporal dependencies of blood pressure data more effectively, resulting in improved prediction accuracy.

This paper is structured as follows: Section 2 outlines the methodology of the proposed CNN-LSTM hybrid model. Section 3 presents the results. Finally, Section 4 concludes with future work directions.

2. Methodology

2.1 Long Short-Term Memory (LSTM) Network:

The LSTM model features a single LSTM layer followed by two dense layers. The input data were organized into sequences of five-time steps, each with one feature. The architecture included 64 units in the LSTM layer, an intermediate dense layer with eight units using ReLU activation, an output dense layer with a single unit, and a linear activation function. The model was trained using the Mean Squared Error (MSE) loss function, and the Adam optimizer with a learning rate of 0.0008 was used for optimization. Hyperparameters, including the number of LSTM units, learning rate, and training epochs, were tuned to enhance the model accuracy, improve generalization, and prevent overfitting. Dropout regularization was applied at a rate of 0.2 is applied. The model was trained for 50 epochs with a batch size of 32. Early stopping with a patience of 10 epochs was employed to monitor the training process, halting when performance on the validation set ceased to improve, thus avoiding unnecessary computations.

2.2 Convolutional Neural Network (CNN):

The CNN model was structured with a convolutional layer, flattening layer, and two dense layers. The convolutional layer employs 64 filters with a kernel size of 2 to extract features from the time-series data. The output from this layer was flattened and passed through a dense layer with eight units and ReLU activation, followed by a final dense layer with a single unit and a linear activation function. The model was compiled using the Mean Squared Error (MSE) loss function and optimized using the Adam optimizer with a learning rate of 0.0008. Hyperparameters, including the number of filters, kernel size, and learning rate, were tuned to optimize performance. Batch normalization was applied following the convolutional layer to enhance the feature extraction and mitigate overfitting. The CNN model was trained for 50 epochs with a batch size of 32. Owing to the sequential nature of the data, data augmentation is not used; instead, L2 regularization is employed in the dense layers to further improve the model generalization.

2.3 CNN-LSTM Hybrid Model:

The CNN-LSTM hybrid model combines Convolutional and LSTM layers to capitalize on both spatial and temporal feature extraction. The architecture starts with a convolutional layer with 64 filters and a kernel size of two, followed by a max-pooling layer with a pool size of two. The output from these layers was then fed into an LSTM layer of 64 units. A final dense layer with a single unit and linear activation function produces the output. The model was compiled using the Mean Squared Error (MSE) loss function and the Adam optimizer with a learning rate of 0.0008. Hyperparameters, including the number of filters, kernel size, LSTM units, and learning rate, were tuned to enhance the model performance and effectively capture both short-term patterns and long-term dependencies. To mitigate overfitting and improve robustness, dropout layers with a rate of 0.3 are applied after both the Convolutional and LSTM layers. The model was trained for 50 epochs with a batch size of 32, and early stopping with a patience of 10 epochs was employed to prevent overfitting and ensure that the model generalized well to unseen data.

2.4 Validation Strategy

Validating the model's performance is necessary to ensure its accuracy and reliability in predicting blood pressure trends. This study employs a multi-dimensional evaluation approach using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). These metrics present a comprehensive assessment of the predictive capabilities of the model and facilitate comparisons with other similar models.

2.4.1 Evaluation Metrics:

2.4.1.1 Root Mean Squared Error (RMSE):

The RMSE is calculated as the square root of the average squared differences between predicted and actual values; thus, a lower RMSE signifies improved model performance. Mathematically,

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \qquad (1)$$

2.4.1.2 Mean Squared Error (MSE):

The MSE is calculated as the average of the squared differences between predicted and actual values, thus, a lower MSE signifies improved model performance.Mathematically,

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \qquad (2)$$

2.4.1.3 R-squared (R^2):

R^2 measures the proportion of variance in the actual values explained by the model's predictions, indicating how well the model fits the data, with values closer to 1 signifying a better fit. R^2 provides insight into the model's explanatory power rather than error magnitude. Mathematically,

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad (3)$$

Where $\hat{y}$ is the predicted value of y and $\bar{y}$ is the mean value of y [24], [25].

3.Results and Discussion

The performance of the LSTM, CNN, and CNN-LSTM hybrid models for continuous blood pressure prediction was assessed using three key metrics: R-squared (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics offer valuable perspectives on each model's accuracy, ability to generalize, and overall predictive performance.

As summarized in Table 1, the CNN-LSTM hybrid model consistently surpassed both the standalone CNN and LSTM models across all three-evaluation metrics (R^2, MSE, and RMSE). This demonstrates its superior predictive accuracy compared to the other models.

METRIC / MODEL	LSTM	CNN	CNN-LSTM
R^2	0.9125	0.8965	0.9197
MSE	0.0045	0.0053	0.0042
RMSE	0.0672	0.0727	0.0649

Table 1. The Performance metrics of Blood Pressure using CNN, LSTM and CNN-LSTM models

3.1 R-squared (R^2):

The CNN-LSTM hybrid model achieved the highest R^2 score of 0.9197, capturing nearly 92% of the variance in the data. The LSTM model also performed well, with an R^2 of 0.9125, which is slightly below that of the hybrid model. The CNN model, with the lowest R^2 score of 0.8965, still demonstrated solid explanatory power.

3.2 Mean Squared Error (MSE):

The CNN-LSTM hybrid model exhibited superior performance with an MSE of 0.0042, followed by the LSTM model with an MSE of 0.0045. The CNN model exhibited a slightly higher MSE of 0.0053, reflecting its comparatively lower prediction accuracy. These results suggest that the CNN-LSTM hybrid model generates more precise predictions than the standalone CNN and LSTM models.

3.3 Root Mean Squared Error (RMSE):

The CNN-LSTM hybrid model exhibited superior performance, achieving the lowest RMSE of 0.0649. This was followed by the LSTM model, with an RMSE of 0.0672, whereas the CNN model had the highest RMSE of 0.0727. These results confirm that the CNN-LSTM hybrid model provides more accurate predictions with smaller deviations from the actual blood pressure values than the other two models.

The results show that the CNN-LSTM hybrid approach outperforms both the standalone CNN and LSTM models in terms of forecasting blood pressure value. By combining the CNN's ability to extract spatial patterns with the LSTM's proficiency in handling temporal dynamics, the hybrid model effectively captures complex patterns in physiological signals. This leads to improved overall accuracy, as shown by the improved R^2 score and lower MSE and RMSE values.

The LSTM model performed well in capturing temporal sequences but slightly lagged behind the hybrid model, suggesting that incorporating convolutional layers can further enhance the predictive power by identifying local patterns in the data. Conversely, despite its relatively strong performance, the CNN model struggled with temporal aspects, reflected in its slightly lower accuracy metrics, which underscores the value of integrating different deep learning techniques for more prediction precision in complex medical datasets. The notable effectiveness of the CNN-LSTM combined approach highlights its potential for practical application in continuous blood pressure monitoring and cardiovascular health management.

4. Concluding Remarks and Future Directions

This study introduced a novel approach for continuous blood pressure prediction using sequential data by integrating Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) into a combined model. The CNN-LSTM hybrid model outperformed the standalone CNN and LSTM models, achieving an R^2 score of 0.9197, an MSE of 0.0042, and an RMSE of 0.0649. These findings highlight the potential of the hybrid architecture for capturing both sequential and spatial correlations, resulting in improved prediction precision.

These findings indicate that combining CNNs and LSTMs enhances the precision of predictions in physiological temporal sequences, such as blood pressure. The potential of the hybrid model to extract complex structures makes it a promising tool for continuous health monitoring, with the capacity to enhance patient care through timely and precise intervention.

Further studies could delve into improving the hybrid model through hyperparameter fine-tuning, expanding it to incorporate additional physiological data, and exploring real-time clinical applications. This work enriches the field of healthcare machine learning, emphasizing the value of advanced predictive modeling techniques to enhance cardiovascular health monitoring.

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