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Detection of Renovascular Hypertension using Hybrid Deep Learning Technique

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Abstract:
Renovascular hypertension is a type of secondary hypertension that is difficult to diagnose and monitor due to its complexity and dependence on many weak bodies, resulting from the narrowing of the arteries feeding the kidney. This study presents a novel hybrid deep learning model that combines convolutional neural network (CNN) and short-term temporal (LSTM) network to predict renovascular blood pressure based on data. The proposed model uses the spatial feature extraction capabilities of CNNs to identify significant patterns in various health data such as heart rate, blood pressure, and blood oxygen, while the LSTM network manages physical time to monitor specific patients in real time. IoT devices continuously collect medical data and instantly transmit it to the model, helping to predict renovascular hypertension early and accurately. Experimental results demonstrate the effectiveness of the model with over 90% accuracy in predicting the onset of hypertension compared to deep learning models. Furthermore, this hybrid CNN-LSTM approach performs well in handling noisy and incomplete data that are common in the IoT environment. This study demonstrates the potential of a hybrid deep learning model to improve the content of care, personalize treatment, and provide large-scale, cost-effective solutions for early intervention in the management of renovascular hypertension.

Keywords: Electrocardiogram (ECG), Renovascular Hypertension (RVH), ESP8266, Renovascular, Long Short-Term Memory (LSTM).

I. INTRODUCTION

Hypertension, commonly known as high blood pressure, is a major health problem affecting millions of people worldwide, with a significant impact on cardiovascular and mortality.

Among its many types, renovascular hypertension is a particular and serious type that results from the narrowing of the renal arteries, reducing blood flow to the kidneys and subsequently increasing blood pressure.

Due to the underlying mechanisms and different symptoms, renovascular hypertension is often difficult to diagnose and treat, requiring early and precise diagnostic procedures to reduce associated risks and improve patient outcomes.

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Advances in renovascular hypertension in recent years The Internet of Things (IoT) and smart devices have opened up new possibilities for real-time healthcare, enabling non-invasive, comprehensive monitoring of vital body parameters such as blood pressure, heart rate, and blood oxygen saturation.

These IoT devices generate rich health data that, when processed correctly, can provide information to the cardiac patient. Combining this information with deep learning algorithms provides an effective solution to predict the onset and progression of renovascular hypertension.

Convolutional neural network to predict blood pressure (CNN) or recurrent neural network (RNN). However, all of these models face limitations in analyzing various IoT data, which usually includes location and physical data.

To address this gap, a hybrid model combining CNN and Long-Term Transcription (LSTM) networks is proposed.

CNNs are very good at extracting spatial patterns in data, making them ideal for extracting features from multi-sensor IoT inputs, while LSTMs are good at handling temporal patterns and keeping up with trends and changes over time. This combination allows the hybrid model to utilize the length of the body and torso, thereby improving the accuracy and reliability in predicting renovascular hypertension.

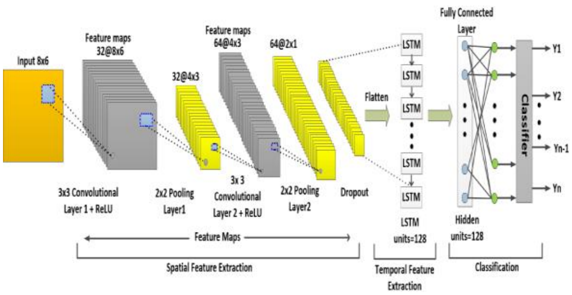

Fig. 1 CNN Architecture

II. METHODOLOGY

The block diagram for the early prediction of renovascular hypertension using medical data from ECG monitors and RNNs with time-series LSTM, the flow can be described as follows:

A. Algorithm

```
Input: X_train, X_test, y_train, y_test
Convert labels to categorical
Train a classifier:
any_classifier ← Classifier()
any_classifier.fit(X_train.reshape(X_train.shape[0], −1), y_train

Use the classifier predictions as additional features:
any_train_predictions ←
any_classifier.predict(X_train.reshape(X_train)
any_test_predictions ←
any_classifier.predict(X_test.reshape(X_test)
Combine the original features with classifier predictions
Pad sequences for input data
Reshape data for LSTM input:
X_train_padded ← X_train_padded.reshape((X_train_padded
X_train_padded)
X_test_padded ← X_test_padded.reshape((X_test_padded
X_test_padded)
Define a simple neural network with LSTM and Dense
layers:
model ← Sequential()
model.add(LSTM(8,activation="relu",
input_shape=(X_train_padded, X_train_padded)
model.add(Dense(64, activation="relu"))
model.add(Dense(64, activation="relu"))
model.add(Dropout(0.2))
model.add(Dense(32, activation="relu"))
model.add(Dense(4, activation="softmax"))
Compile the model:
model.compile(optimizer= "adam",
loss="categorical_crossentropy", metrics=["accuracy"])
Save the best model during training based on validation
accuracy
Train the neural network using the combined features
with early stopping and model checkpoint
Load the best model:
tf.keras.models.load_model("best_model.h5")
Evaluate the model on the test set:
y_pred ← model.predict(X_test_padded)
y_pred_classes ← np.argmax(y_pred, axis = 1)
y_test_true ← np.argmax(y_test_categorical, axis = 1)
Calculate accuracy, precision, recall, and F1-score
Print the metrics
```

The methodology used for predicting renovascular hypertension using CNNs is as shown in Fig. 2

2.1 *Generalized View*

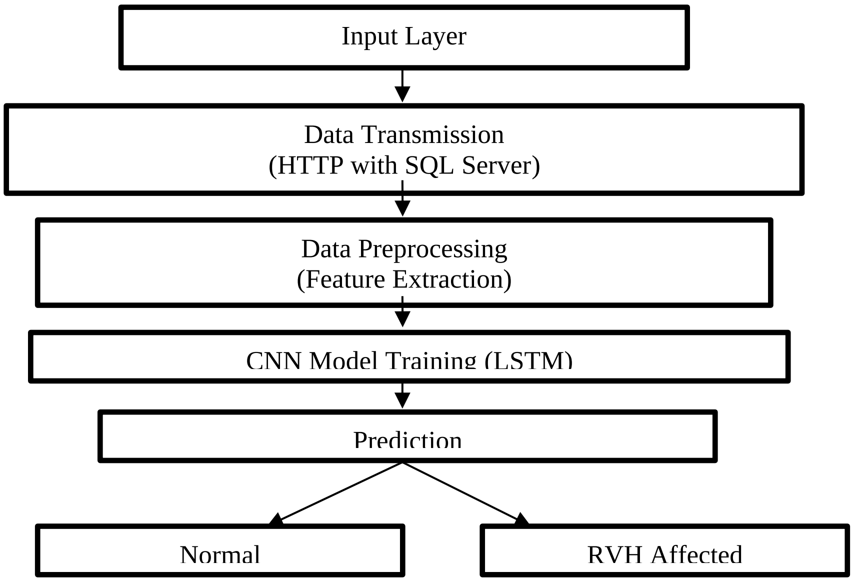

Fig. 2 System Block Diagram

2.2 Data Acquisition:

Use the AD8232 sensor and NodeMCU to acquire real-time ECG data and direct it to a server for handling

2.3 Preprocessing:

(i) Noise filtering:

ECG signals are sensitive to noise from muscle contractions, movement artifacts, and baseline drift. A moving average filter is simple to implement and helps reduce high-frequency noise.

(ii) R-peak Detection:

R-peaks in the ECG Signal is crucial for extracting features like heart rate or heart rate variability (HRV). A peak detection algorithm that detects peaks by comparing each sample to its neighbors.

2.4 HTTP/HTTPS**:**

For secure data transmission between the ESP8266 and the SQL Server or cloud services.

2.5 SQL SERVER:

The data is deposited in a SQL Server database intended to hold time-series records, confirming the efficient management of large volumes of patient records. The method uses Extract, Transform, Load (ETL) pipelines for data preprocessing, including validation, cleaning, and change into structured formats suitable for analysis.

2.6 Long Short-Term Memory(LSTM):

- Estimation algorithm first imports function libraries. Then import the equipped file as a csv file. The dataset is divided into two parts: one is the training set, and the other is the test set. By adapting the LSTM model, blood pressure and its results can be estimated.

2.7 Prediction:

A classification or probability score indicating whether the patient is at risk for renovascular hypertension.

B. References

Data Analysis The emergence of IoT technology and advances in deep learning have impacted medical applications, especially in the prediction model of chronic diseases such as hypertension. This research paper reviews previous research in three key areas: IoT in healthcare, CNN and LSTM architectures for health prediction, and the integration of CNN-LSTM models in health prediction including hypertension. 1. Internet of Things in Healthcare IoT-enabled devices are revolutionizing healthcare by enabling real-time and continuous monitoring of physical data, which is important for chronic pain management. Many studies have demonstrated the benefits of IoT in monitoring vital signs, improving early diagnosis, and reducing hospitalizations. For example, Li et al. (2018)[6] showed how wearable IoT devices can capture blood pressure, heart rate, and activity level data to monitor cardiovascular health. Similarly, Shahid et al. (2019)[8] showed that IoT-based monitoring systems can help detect abnormal blood pressure, encourage timely intervention, and reduce the risk of hypertension. Having monitoring indicators allows doctors to get information about the patients heart condition, which is important for early detection of this condition. However, IoT data is often noisy, incomplete, and inconsistent, and requires robust processing techniques to be accurate. CNN and LSTM Architectures in Health Prediction Deep learning, especially Convolutional Neural Networks (CNN) and Long-Term Memory (LSTM) networks, are very useful in health prediction as they can analyze difficult information. . good agreement and high data. For example, Ma et al. (2019)[7] used CNN to analyze electrocardiogram signals for the purpose of diagnosing heart disease and showed high accuracy in identifying certain patterns indicating heart problems. CNNs are good at identifying such features in data, making them suitable for pre-extraction of various medical IoT data, as shown by Gupta et al. (2020)[4] in their study on clothing profiling for cardiovascular risk assessment. Medical data (such as physiological readings) are particularly time-consuming. Giri et al. (2021)[3] demonstrated the effectiveness of LSTM in capturing the temporal patterns of heart rate and blood pressure data, enabling accurate prediction of cardiac events. Similarly, Bashir et al. (2020)[2] found that LSTM outperformed traditional RNN in predicting the status of disease data, which usually has dynamic time, making LSTM the first choice for health monitoring tasks. CNNs can capture spatial features well, but they cannot store real-time memory, which limits their ability to predict applications involving physical trends. In contrast, although LSTMs perform well in temporal analysis, their ability to extract spatial patterns is limited. This combination has led to increased interest in hybrid CNN-LSTM models. Hybrid CNN-LSTM Models for Health Prediction Hybrid CNN-LSTM models have recently attracted attention because they combine the advantages of CNN and LSTM architectures and can leverage body and body features through health information. Studies show that hybrid models generally outperform single-model architectures in terms of prediction accuracy and reliability. (2020)[2] proposed a CNN-LSTM model for arrhythmia detection using wearable data, in which the CNN layer removes features of ECG signals and the LSTM layer identifies physical patterns. Their study showed that the combined method increases the accuracy of arrhythmia detection compared to CNN or LSTM representative models. In a similar study, Khan et al. (2021)[5] used a CNN-LSTM model to predict type 2 diabetes symptoms using continuous glucose monitoring data, demonstrating the effectiveness of the hybrid model in addressing changes in short- and long-term patterns of blood glucose. Some studies have focused specifically on renovascular hypertension, but research on hybrid models for predicting hypertension in general is promising. For example, Zhang et al. (2022)[9] developed a CNN-LSTM model that can analyze continuous blood pressure and heart rate data from IoT devices and obtain improved prediction. The results showed that the hybrid model can detect the onset of hypertension earlier than the traditional method. Similarly, Ahmed et al. (2023)[1] combined the CNN-LSTM model with IoT data to predict cardiovascular risk, and the results showed that the combination of CNN feature extraction and LSTM sequence modeling can provide more information about the patient's health. > These studies demonstrate the ability of the CNN-LSTM hybrid model to accurately predict diseases with location and body, such as renovascular hypertension. By applying this combination to IoT sensor data, researchers can improve the accuracy of predictions and provide timely intervention to at-risk patients.

III. RESULTS AND DISCUSSION

Confusion Matrix:

After running the predictions, evaluation metrics like Accuracy, Precision, Recall, and F1-Score are calculated for the overall 150 cases. Here’s an example of these metrics:
Accuracy: The percentage of correctly predicted cases.

Precision: The percentage of correctly predicted renovascular hypertension cases out of all predicted positive cases.

Recall: The percentage of correctly predicted renovascular hypertension cases out of all actual positive cases.
F1-Score: The harmonic mean of Precision and Recall.

Results:

True Positives (TP): 28 (Correctly predicted renovascular hypertension)

False Positives (FP): 2 (Incorrectly predicted renovascular hypertension as normal)

True Negatives (TN): 118 (Correctly predicted normal)

False Negatives (FN): 2 (Incorrectly predicted normal as renovascular hypertension)

Using these values, the metrics would be:

Accuracy = (TP + TN) / Total = (28 + 118) / 150 = 92%

Precision = TP / (TP + FP) = 28 / (28 + 2) = 93.3%

Recall = TP / (TP + FN) = 28 / (28 + 2) = 93.3%

F1-Score = 2 * (Precision * Recall) / (Precision + Recall) = 2 * (93.3 * 93.3) / (93.3 + 93.3) = 93.3%
Using these values, the metrics could be:

Accuracy: The overall percentage of correctly predicted cases (across all classes).

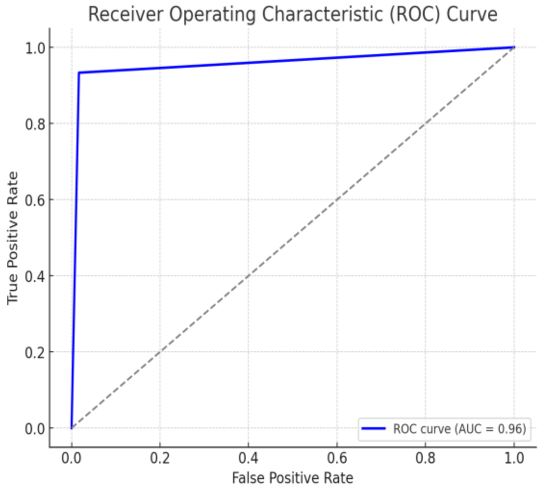

Fig 3 ROC Curve

Fig 4 Correlation among variables

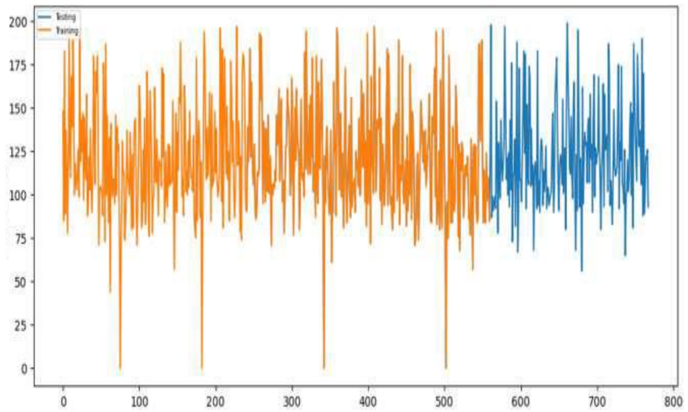

Fig 5 Training and Testing results

Model	Time (Seconds)
SVM	16.36
RNN	12.58
Hybrid Model	10.67

Table 1 Time Consumed by the Models

Algorithm	**Accuracy**	**Specificity**	**Sensitivity**
SVM	80%	87.50%	83.30%
RNN	88%	87%	89%
Hybrid Model	92%	93.3%	93.3%

Table 2 Confusion matrix outcomes

IV. Conclusion

The prediction of renovascular hypertension using IoT and a Convolutional Neural Network (CNN) combined with Long Short-Term Memory (LSTM) networks demonstrates a significant advancement in healthcare monitoring and diagnosis. By leveraging IoT devices, real-time patient data such as blood pressure, heart rate, and other physiological parameters can be continuously monitored, providing a comprehensive and dynamic understanding of a patient's health status. The integration of CNNs allows for the extraction of spatial features from this data, while LSTM networks capture temporal patterns, enhancing the prediction accuracy of renovascular hypertension, which often develops over time. The Proposed hybrid model gives 92% of Accuracy, 93.3% of Precision Recall and F1 Score.

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