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RESEARCH ARTICLE

HYCARE-NET: IOT-ENABLED DEEP LEARNING FOR REAL-TIME HYPERTENSION MONITORING

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Abstract – Hypertension is a chronic condition that increases the risk of developing several causes, including cardiovascular diseases, cerebrovascular strokes, kidney failure, and hypertension attacks. Hypertension-related information must be tracked and evaluated in real time in order to mitigate these dangers. Real-time hypertension diagnosis and blood pressure (BP) monitoring are possible with Internet of Things (IoT) assisted health monitoring systems. In this paper, novel hypertension healthcare monitoring using deep learning network (HyCare-Net) technique in IoT has been proposed. The proposed method utilizing the Convolutional Neural Network for feature extraction to enhance classification accuracy. A Ghost Net classification technique classifies the extracted feature into three classes such as Low, Normal, High classes. Measures including specialty, f1score (F1S), accuracy, precision (PR) recall (RC) are used to assess the suggested approach. Compared to current models, experimental results using hypertension datasets show higher accuracy. The accuracy of the HyCare-Net approach in the hypertension dataset is 1.5%, 3.5%, and 7.5% higher than that of the current SB IOT-MPH, SPMR-DL, and IDOCNN techniques respectively.

Keywords *– Internet of Things, Convolutional Neural Network, Deep Learning, Hypertension Monitoring, Ghost Net classification.*

1. INTRODUCTION

Devices that connect and share data with other devices and systems via the Internet or other communication networks are referred to as IoT devices. These devices may use sensors, software, and other technologies. IoT is made up of a variety of physical objects, including embedded devices that are combined with diverse software and technologies [1,2]. It alludes to the Internet's upcoming generation. This technology turns into a workable way to deliver effective healthcare remotely. IoT facilitates healthcare and is necessary for many applications that track medical services [3,4].

Healthcare is essential to maintaining public health, it stands out as a critical issue. Individual health, economic productivity, and social stability are just a few of the facets of society that are impacted by the availability of quality healthcare services [5,6]. Many illnesses and health problems still plague people all over the world, and if they are not identified early and treated promptly, they can worsen and even cause death. The patient healthcare system monitors how a person's body functions on a daily basis and automatically alerts clinics or hospitals to any changes in a patient's condition [7-9].

One of the most common cardiovascular conditions is hypertension it affects 22% of adults over the age of 18 worldwide and claims the lives of around 9.4 million people annually. [10] Hypertension can cause serious side effects like myocardial infarction, stroke, and chronic renal disease if it is not properly identified and treated [11,12].

Compared to the traditional sphygmomanometer-based approach, smartphone-based diagnosis of hypertension using sensors can be less expensive, quicker, and easier to acquire. By solving the present challenges of diagnosing hypertension without the use of additional medical equipment, it also has the potential to raise the standard of telemedicine [13]. The following are the main contributions of the suggested work:

- The main objective of the study is to provide an efficient method for IoT-based hypertension monitoring in order to provide patients with early warnings.
- To improve data quality, the patient's body temperature, heart rate, and blood pressure are first pre-processed using data cleaning, normalization, and discretization.
- The HyCare-net technique leverages feature extraction by using CNN model to capture features efficiently and raise the classification model's accuracy.
- The collected features are then used to train the Ghost Net model for classification, allowing it to correctly classify data into three classes such as low, normal, and high.

- The effectiveness of the suggested technique is valued utilizing parameters like accuracy, recall (RC), f1-scores, specialty.

The remainder of the document is arranged as follows. The literature review is thoroughly discussed in part II. A description of the created IoT hypertension monitoring system is provided in part III. The results and observations of the experiment are presented in part IV. The conclusion and next steps are in part V.

2. LITERATURE REVIEW

In 2022, de Souza, P.L.,[14] suggested a IoT based system for Monitoring Hypertensive Patients (SB IoT-MPH) that enables prompt and effective vital sign monitoring. Using a variety of sensors, it records the patient's position, sends data to mobile apps both offline and online, and notifies caregivers of any serious health situations

In2023, Talaat, F.M. and El-Balka, R.M.,[15] suggested a Wireless channels, wearable technologies, and other remote equipment provide affordable healthcare monitoring. For this categorization, Random Forest and OSM are the most appropriate, followed by XG Boost and Decision Tree. Because IoT-enabled medical monitoring can increase the precision and effectiveness of diagnosis and treatment, the study's conclusions have implications for the future of healthcare services.

In 2023, Attiyah, R., [16] suggested an innovative intelligent monitoring device for fontal and maternal signals in high-risk pregnancies. Enhanced single-dimensional convolutional neural network (1DOCNN) for improved categorization and forecasting of various maternal and fetal emergencies. 96% precision, 96.5% F1-score, 96% recall, 96.5% accuracy and 96.2% specificity were best results obtained when predicting the normal and pathological condition of the mother and fetus.

In 2024, Ratta, P. and Sharma, S [17] suggested a decentralized, blockchain-based system to address privacy, security, and diabetes monitoring issues in IoT devices. When it came to diabetes classification, the AdaBoost model had the highest predictive accuracy (92.64%), followed by the Decision Tree model (92.21%). The difficulties, include technological problems like security and interoperability, ethical concerns, and data compilation.

In 2024, Sundas, A., et al [18] suggested a first DL-based Smart Patient Monitoring and Recommendation (SPMR) system to guarantee ongoing monitoring and prediction insights about a patient's true health stage. The final results are K- NN achieves 92% accuracy, DT achieves 95% accuracy, NB achieves 85% accuracy, and SVM achieves 80% accuracy.

In 2024, Hannan., A et al [19] suggested a wearable smart and early heart attack detection device used a hybrid computing architecture and a decentralized computational phenomenon to improve response time and reduce latency in order to identify heart attacks in their early stages for patients. AdaBoost is 85% while SVM is 91%.

In 2024, AL Zakari, S.A., [20] suggested an approach improves prediction accuracy by integrating physical patient data with Electronic Clinical Data (ECD) from comprehensive medical records and routine medical monitoring for the efficient analysis of large datasets and the extraction of crucial features. Using our method, it achieved a higher prediction accuracy of 99.4% than naive Bayes, decision trees, and random forests.

3. PROPOSED METHOD

In this portion, a novel HyCare-Net approach has been proposed to monitor patient hypertension accurately. Initially the datas are gathered from patients using sensors and pre-processed utilizing methods such as Normalization, Data cleaning and discretization to enhance the data quality. After pre-processing the essential features are extracted using CNN model. Finaly the extracted features are fed into ghost net which classifies into three classes such as Normal, bit high and very high. In Figure 1, the HyCare-Net approach's overall workflow is displayed.

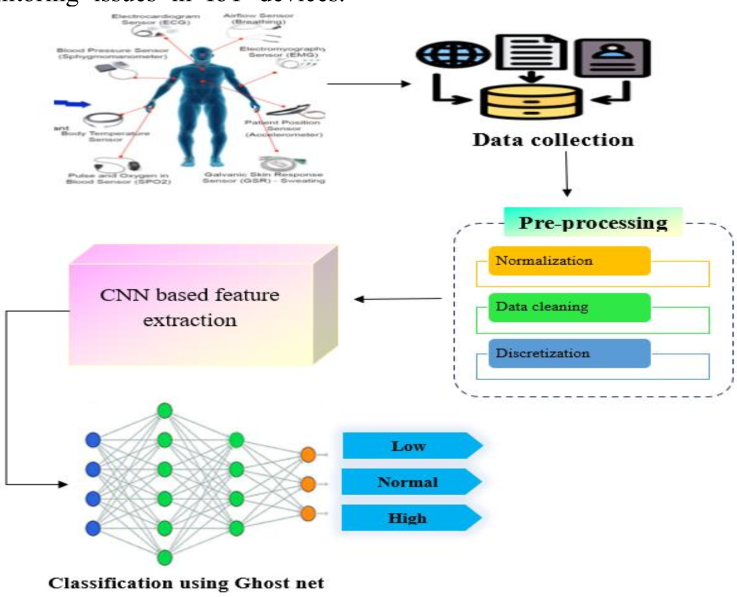


Figure 1. Proposed Methodology

3.1. Sensor data acquisition

Sensors attached to the patient's body are used to gather data from the patients. These sensors include the oxygen sensor, which determines the oxygen saturation level of the patient, the patient's blood pressure is measured by the pressure sensor, their body temperature is measured by the temperature sensor, and their heart rate is tracked by the heart rate sensor. This sensor is used to collect the data.

3.2. Pre-Processing

The preprocessing steps of normalization, data cleansing, and discretization are applied to the gathered data. Data cleaning corrects the data, such as filling in missing information, and normalization places the value within a predetermined range. Data are categorized by discretization. Accurate data classification requires a pre-processing step**.**

3.2.1 Normalization

The process of converting values measured on various scales to a conceptually similar scale is called normalization. Numerous methods exist for normalization, such as baseline, min-max, and z-score normalization. Each sensor collects a wide variety of resistance values, which, if appropriately normalized, can aid in producing more accurate test data predictions.

3.2.2 Data Cleaning

Data cleaning entails fixing errors, eliminating outliers, and adding missing values. Sensor datasets that contain broken sensor data and settling time zones must be cleansed. Errors in the data collection process or problems with the sensor itself are recorded as broken sensor data.

3.2.3 Discretization

Discretization of continuous predictors is a popular method for preprocessing data, which is an important step before data is entered into multiple machine learning classifiers for learning. To enable effective dataset integration, these models usually require the input data to be pre-processed into discrete numerical values. a technique where the continuous feature is split up into equal segments. It is necessary to decide the number of intervals in advance

3.3. Feature extraction via CNN

The convolutional neural network (CNN) has generated a great deal of interest due to the advancement in computer power and training methods. CNNs (Convolutional Neural Networks) identify hidden patterns in data, apply filters to find patterns, and process each layer. The function Relu was used to highlight strong signals and retrieve the most crucial data attributes for classification. The mathematical model outlined in Equation (1) is followed by a conventional CNN.

$$Z_{xy} = (M * N)_{xy} = \sum_q \sum_p M_{(x+q)(y+P)} N_{qp} \qquad (1)$$

Equation (1) states that the sensor features are extracted by the hidden layers via convolution processes, represented by M. A pooling layer that lowers the range comes after it. Zxy is the output feature map at point (x, y) (x, y), and M is kernel of p× q p × q. Ultimately, the convolutional procedure extracted the features. In the following stage, these retrieved characteristics are fed into the ghost net classification model.

3.4. Classification using ghost net

The patient data is divided into three classes by the Ghost Net model using the retrieved features as input. Bit high, quite high, normal. This method swiftly and precisely classifies the data. As illustrated in figure 2, the convolutional layer-based mapping is initially used in the Ghost module. Ghost Net uses the two routes listed below:

Primary Path: Primary Path: This path serves as the primary convolutional operation, typically a depth-wise separable convolution. Since depth-wise separable convolutions isolate spatial filtering from channel-wise filtering, they are computationally less expensive than ordinary convolutions. The feature mapping obtained through the primary path is expressed as:

$$Fm = B * d + g \qquad (1)$$

In this case, the feature map is represented by Fm, bias by B ∗d, and conventional filters by g.

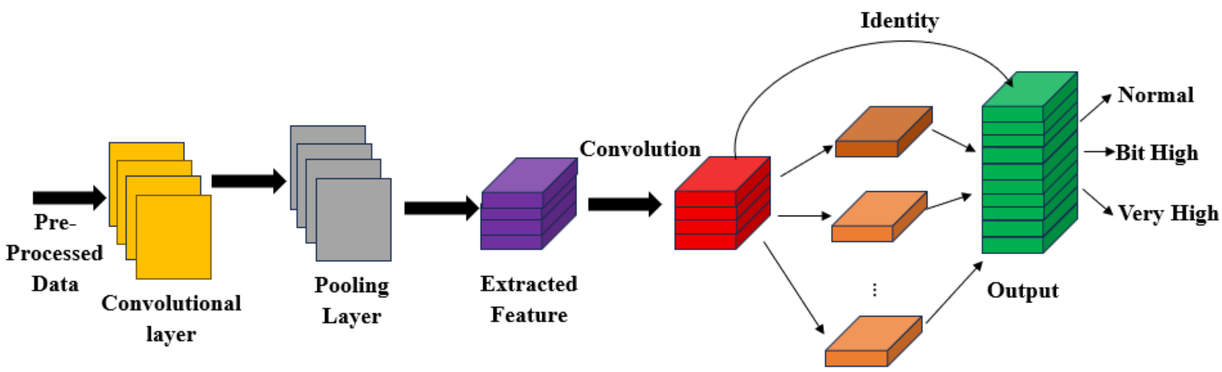


Figure 2. Classification methodology

Ghost Path: The ghost path is inexpensive and shallow. The term "low-complexity operation" is frequently used. Other, less computationally costly aspects are captured via the ghost path. The network can become more efficient and gain higher representational power by combining data from both pathways. The feature mapping that was acquired using the ghost path is expressed as follows:

$$\mathrm{Fm} = B * d' \quad (2)$$

where d' is the filter used in the ghost path. The Ghost Net's output is passed into the softmax and fully connected layers, which classify the data into Normal, Bit High, and Very High.

4. RESULTS AND DISCUSSION

This section explores the effectiveness of the suggested strategy using a range of evaluation measures and gives the experimental findings. Here, the suggested categorization model is implemented using a Python programming tool. Accuracy, precision, recall, F1-score, and specialization are the evaluation metrics used in the suggested approach.

4.1 Dataset Description

Data is retrieved from Kaggle HBP and is available [web]: www.kaggle.com/datasets/jayaprakashpondy/blood-pressure.

4.2. Evaluation Metric

This section explains the measures that were used to evaluate the suggested approach. The effectiveness of the recommended strategy has been evaluated using the F1-Score, Recall, Precision and Accuracy measures.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP}$$

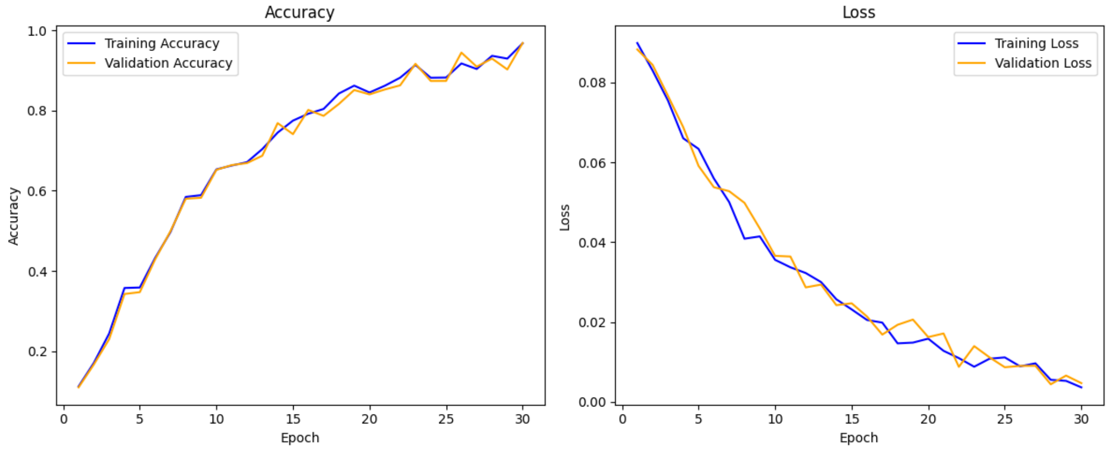
$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$$

$$\mathrm{F1-score} = \frac{2*(\mathrm{PR}*\mathrm{Recall})}{(\mathrm{PR}+\mathrm{Recall})}$$

$$Recall = TP/(TP + FN)$$

4.3 Performance Analysis

According to the experimental results, the suggested HyCare-Net technique has been compared with current techniques for detecting patient's hypertension, including SB IOT-MPH, SDMR-DL, IDOCNN.



(a) (b)

Figure 3. Accuracy vs Loss

The accuracy vs. loss in Figure 3 demonstrates how effectively the suggested HyCare-Net model learned from the dataset. Using 10 epochs, the model's validation accuracy was 99.77% with a validation loss of 0.0055%. These Figures illustrate the model's efficacy by showcasing its capacity to detect intrusions. The moderate loss numbers also show that learning was successful and that overfitting was kept to a minimum throughout the training period.

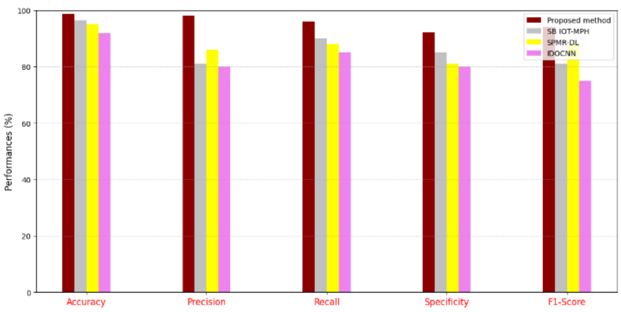


Figure 4. Accuracy and Loss curve

The performance study of categorization classes using the Hypertension dataset is shown in Figure 4. For the Hypertension dataset, the recommended method's F1-Score, accuracy, recall, precision, and specialty are 96.61%, 98.73%, 96.44%, and 93.98%, respectively.

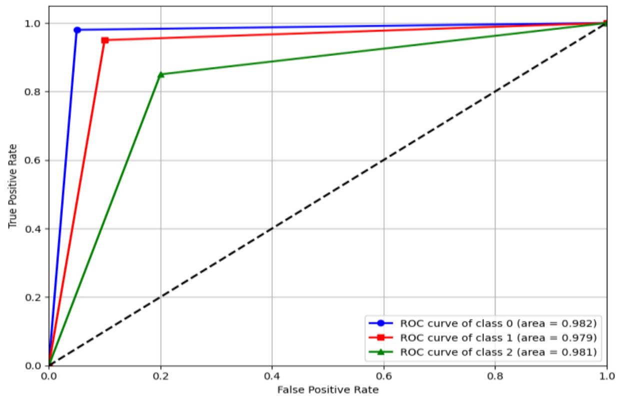


Figure 5. Roc Analysis dataset

The ROC of hypertension monitoring outcomes using the hypertension dataset is shown in Figure 5. In comparison to the hypertension dataset, HyCare-Net's parameters produced a comparatively high AUC of 97.9 for normal cases and 98.4 for high cases.

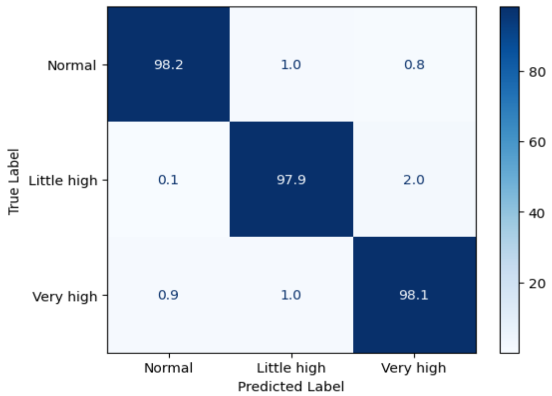


Figure 6. Confusion Matrix

For classification tasks, Figure 6 shows confusion matrices with performance predicted labels on low, normal, and high 98.45% of labels are identified, with 1.08% being classified as normal and 1.20% as somewhat elevated. The classifier performs well across all datasets, especially when it comes to tracking hypertension.

5. CONCLUSION

This study suggests a new HyCare-Net method for efficiently tracking patients' hypertension. The CNN model is utilized for feature extraction in order to efficiently capture features and improve the classification model's accuracy. By feeding these extracted features into the Ghost Net model, the network is able to classify data reliably into three classes: low, normal and high. In addition to increasing patient protection, this method raises awareness of hypertension and advances the monitoring of hypertension. The proposed method is evaluated using f1score, recall, accuracy, and precision. For the Hypertension dataset, the proposed method's F1-Score, accuracy, recall, precision, and specialty are 96.61%, 98.73%, 96.44%, and 93.98%, respectively. The accuracy of our HyCare-Net methodology is 1.5%, 3.5%, and 7.5% higher in the hypertension dataset than the current SB IOT-MPH, SPMR-DL, and IDOCNN methods. The system can be further developed by integrating it with artificial technology to create an intelligent system that can use data patterns from reading data from system devices to predict the health of older individuals.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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