RESEARCH PAPER

An ML-Driven IoT Framework for Early Detection of Chronic Diseases Using Wearable Sensors

Dr. Kallepalli Rohit Kumar[1*], Dr. V. S. Ramakrishna[2], Mr. Ramesh Kothapalli[3], Praveen Tumuluru[4]

[1*] Department of Computer Science and Engineering, Vignan's Institute of Information Technology, Visakhapatnam, Andhra Pradesh, India. Email: dr.rohithkumar@vignaniit.edu.in (Corresponding Author)

[2] Department of Computer Science and Engineering, Bonam Venkata Chalamayya Engineering College, Odalarevu, Andhra Pradesh, India. Email: vsrkaws@gmail.com

[3] Department of Computer Science and Engineering, Aditya University, Surampalem, Andhra Pradesh, India. Email: rameshk@adityauniversity.in

[4] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India. Email: praveenluru@gmail.com

Received: 2nd Mar, 2026 | **Revised:** 14th Mar, 2026 | **Accepted:** 4th Apr, 2026 | **Available Online:** 20th Apr, 2026

ABSTRACT

The rise in chronic conditions, like cardiovascular disorders, diabetes, and kidney disease, among others, have contributed to the increase in mortality worldwide since these conditions go unnoticed until too late when proper monitoring and early detection are not performed. As a solution to the problem mentioned above, the present study proposes an IoT architecture that uses machine learning techniques to help detect chronic diseases in real-time. First, the proposed system involves the application of a CKD dataset coupled with features obtained from wearable sensors. Subsequently, data pre-processing and feature extraction are carried out to prepare the data. Afterward, an Input Specific Neural Network (ISNN) is applied to classify patients as either having CKD or not CKD. This classifier helps in achieving accurate classification, reduces computational cost, and increases the adaptability of the input data types. The proposed method implemented in python. According to the experiment results, the proposed model gives better results than CNN, DNN, and DL models in terms of recall 96.2% and precision 97.8%.

Keywords: Chronic Diseases, Input Specific Neural Network, pre-processing, cardiovascular disorders, CKD.

How to cite this article: Kumar KR, Ramakrishna VS, Kothapalli R, Tumuluru P. An ML-Driven IoT Framework for Early Detection of Chronic Diseases Using Wearable Sensors. Int J Drug Deliv Technol. 2026;16(33s):536-540. DOI: 10.25258/ijddt.16.33s.65

Source of support: Nil.

Conflict of interest: The authors declare no conflict of interest.

1. Introduction

Some of the common chronic diseases, such as heart problems, diabetes, and respiratory ailments, rank amongst the major causes of death around the world, contributing to a substantial number of deaths annually. Recent studies indicate that non-communicable diseases account for about 70% of all deaths across the globe, with an alarming rise in the prevalence of the same caused by various reasons such as inactive lifestyles, aging population trends, and environmental influences. In this regard, early diagnosis can be critical in helping avoid complications, thereby ensuring better health outcomes. The convergence of Machine Learning (ML) technology with Internet of Things (IoT)-supported wearables is an innovative approach towards monitoring patients' health continuously.

Heart disease, diabetes, respiratory diseases, and other chronic ailments are some of the top killers across the globe, contributing a major share of all deaths that occur annually. Statistics from recent health studies suggest that over 70% of all deaths across the world result from non-communicable ailments, which have been steadily growing in prevalence owing to lifestyle factors like a sedentary life, old age, and the environment, among others. Early detection is therefore key in avoiding potential complications and ensuring better treatment results. ML integrated with IoT devices in the form of sensors worn on the body has proved effective in health monitoring and predicting risks.

2. L Recent Works

Adelusi et al.[6] have developed a machine learning-based approach using a sensor-based wearable system that can detect non-communicable diseases by continuously monitoring the health status of patients. In this study, data collected through smart devices have been analyzed using techniques such as CNN and RNN along with techniques such as noise removal and feature extraction. But some problems, such as privacy issues and lack of standardization, have hindered its practical implementation..

Adelusi et al [7] have come up with an intelligent machine learning predictive model to diagnose cardiovascular diseases through electronic health records and wearables data. This study has used various data sets like Framingham Heart Study and MIMIC-III as well as different algorithms such as random forest, support vector machines, and gradient boosting. However, some challenges with the study include lack of diverse population data, temporal data analysis, and requirement of good data quality.

Hosain et al.[8] have come up with a healthcare model that uses IoT and biosensors to monitor patients and detect chronic illnesses. This research has employed a systematic review of studies available in scientific databases like IEEE Xplore, PubMed, and Science Direct, where we have concentrated on the use of IoT and biosensors in monitoring diseases. This study faces some limitations including difficulty in implementation, data accuracy problems, and scaling issues among others.

Wn et a.[9] has enabled the development of a comprehensive and scalable service in precision health that involves wearable devices, environment data, and telecare through AI technology to predict chronic diseases. This study has involved data analysis involving 1,667 patients for 24 months and the use of machine learning and deep learning algorithms to develop a modular model of predicting diseases like obesity, panic disorder, and COPD. However, this study has shortcomings that include reliance on data generation, difficulty in data integration, and scalability problems.

Material et al.[10] have conducted research on user acceptance and issues concerning new wearable health sensors for chronic illness monitoring. In this research, a survey data set comprising 448 participants was utilized to analyze the responses in relation to gadgets like environmental monitoring wristbands and ECG chest stickers. This research is subject to several limitations including dependence on the opinions of the users, biasness in the data set, and lack of clinical validity in real-time for the wearable gadgets.

3. Research Methodology

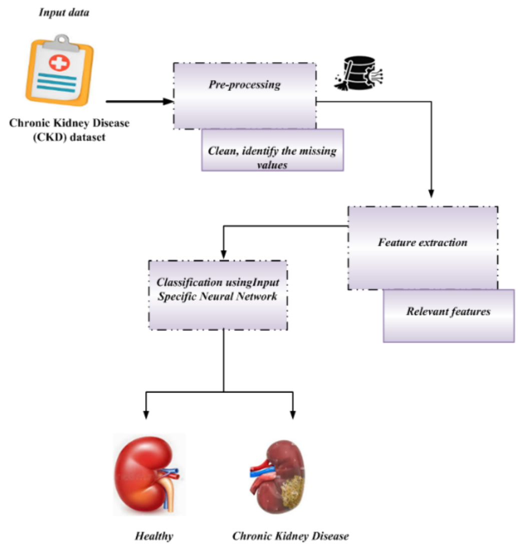

Figure 1: Block Diagram of Proposed method.

3.1 Data description

The suggested approach takes advantage of the Chronic Kidney Disease dataset, which comprises about 400 patient instances, with a set of several clinical features like blood pressure, specific gravity, albumin, sugar, blood urea, serum creatinine, sodium, potassium, and hemoglobin, along with the target class that shows whether or not a disease occurs. The dataset is processed to guarantee uniformity and normal distribution of its features since there are no instances with missing features. In terms of building a machine learning model, the dataset is divided into two parts in the proportion of 80 to 20; thus, the first 80 percent of the dataset is utilized to build the ML model, while 20 percent is intended for its testing.

3.2 Data Pre-processing

In the proposed methodology, data preprocessing takes place to guarantee that the data quality is up to the mark for ML algorithms. In this regard, the dataset is first checked for correctness due to the absence of missing values, after which the scaling process takes place to make the data uniform for numerical features such as blood pressure, serum creatinine, and hemoglobin levels. The red blood cell feature is converted to numeric values and only important health indicators are kept using feature selection methods.

3.3 Feature Extraction

This is done in order to enhance the accuracy of the machine learning models by extracting relevant features from the wearables sensor dataset, such as important physiological parameters like X-axis, Y-axis, Z-axis, electrodermal activity (EDA), heart rate (HR), and body temperature (TEMP). These features contain important information regarding physical activities, stress level, and other important parameters of vital signs. Extracted features are further passed on to the classification phase for early disease detection using the ML-driven IoT system framework.

3.4. Detection and Classification Using Input Specific Neural Networks (ISNN)

Detection and classification in the proposed system are performed using Input Specific Neural Networks (ISNN), which are chosen for their ability to adaptively process heterogeneous input features such as physiological and sensor data. ISNN improves classification accuracy by focusing on the most relevant features while reducing computational complexity. The model classifies the input data into two classes: ckd (chronic kidney disease) and no_ckd (normal), enabling efficient and reliable early disease detection within the proposed ML-driven IoT framework.

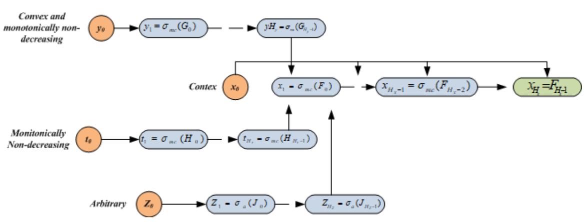

Figure 2: Architecture of ISNN.

The bias term, which allows the model to shift the activation function to better fit the data, is express equation (1)

$$X_{H_x} = \sigma_{mc}(\mathbb{F}_{H_x-1}) \quad (1)$$

Where, X_{H_x} This represents the output vector of the current hidden layer H_x, σ_{mc} is represented into denotes a Multi-Channel Activation Function.In standard neural networks, you might use a single activation like ReLU or Sigmoid, is express equation (2)

$$\frac{\partial^2 x_1}{\partial x_0^2} = W_o^{[xx]^T} . (\sigma''_{mc}(\mathbb{F}_0)^{\,T} . J). W_0^{[xx]} \quad (2)$$

Where, $\frac{\partial^2 x_1}{\partial x_0^2}$ is represented into the Hessian. It measures the "curvature" of the error surface. While a first derivative tells you the slope, this second derivative tells you how quickly that slope is changing. J is represented into usually represents an all-ones vector or a Jacobian-related identity term used to maintain the correct dimensionality during matrix multiplication, is express equation (3)

$$\mathbb{G}_h = \left(y_h W_h^{[yy]^T} + b_h^{[y]}\right), \quad h = 0, \dots\dots, H_y - 1 \quad (3)$$

Finally, the classification segment produces the output by categorizing the input data into two classes, ckd and no_ckd, based on the learned patterns from the ISNN model. The predicted results enable accurate identification of disease presence, and the final output is forwarded to the decision support system for risk assessment, alert generation, and further clinical interpretation within the proposed ML-driven IoT framework.

4. Result and Discussion

This section describes the evaluation and discussion of the proposed method, where its performance is evaluated and compared to existing approaches like CNN, DNN, and DL. The experiment is conducted with Python programming language (version 3.12.12) running under Windows 10 operating system using the proposed FTA-NET architecture that was trained using Deep Weeds dataset. High-end computational resources used in conducting the experiment included 64 GB RAM, Intel Core i9-13900K CPU, and 500 GB SSD Storage.

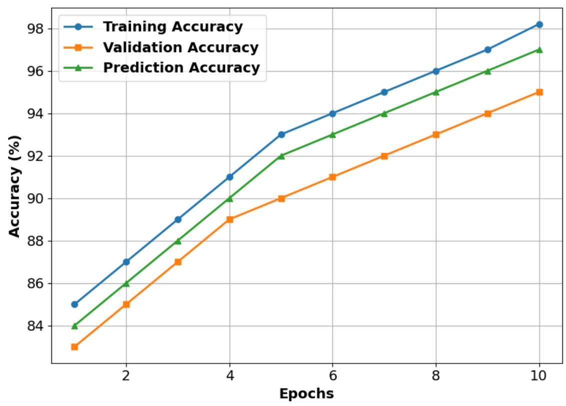

Figure 3 : Analysis the accuracy training and validation.

As demonstrated in Figure 3, there is an analysis of performance based on training, validation, and prediction accuracy for 10 epochs. It can be observed that there is consistency in performance, which means that training accuracy ranges between 85% to 98.2%, validation accuracy varies from 83% to 95%, and prediction accuracy ranges between 84% to 97%. These figures indicate that there is learning of data without any overfitting in the model, hence, showing good generalization ability of the proposed ML-based system.

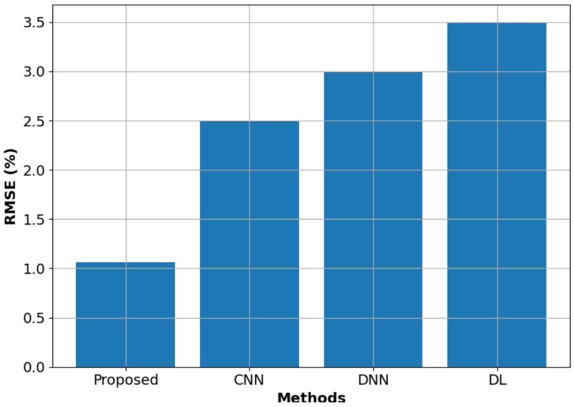

Figure 4 : Analysis the RMSE with proposed and exiting

Figure 4 shows the result of RMSE comparison for the proposed approach and existing techniques. In particular, the proposed model gives significantly low RMSE results with 1.06% as opposed to 2.5% in CNN, 3.0% in DNN, and 3.5% in DL techniques. From this point of view, it is clear that the performance of the proposed technique is much more accurate and reliable as compared to the existing deep learning based techniques.

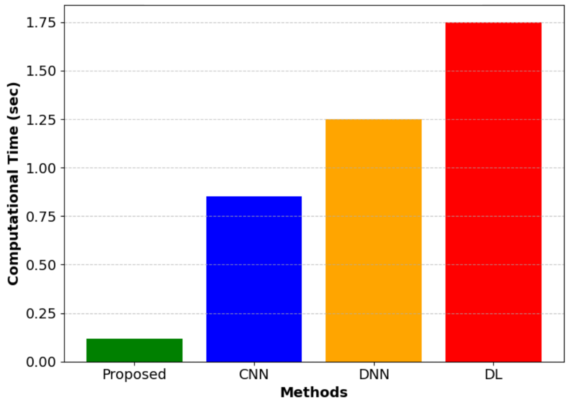

Figure 5 : Analysis the Computational time with proposed and exiting.

The computational time comparison between the proposed algorithm and the other existing algorithms is shown in Figure 5. The proposed technique has obtained the shortest computational time of around 0.12 seconds, proving its superiority over the existing techniques in terms of speed. CNN has taken around 0.85 seconds, which is almost seven times slower than the proposed model, whereas DNN has taken 1.25 seconds, being ten times slower than the proposed technique. The DL technique has registered the maximum computational time of about 1.75 seconds, which is fourteen times larger than that of the proposed algorithm.

Table 1: Comparison analysis of proposed and exiting.

Method	Recall (%)	Precision (%)
CNN (Existing)	89.5	91.2
DNN (Existing)	91.3	92.7
DL (Existing)	93.6	94.1
Proposed Method	96.2	97.8

The proposed approach far surpasses the conventional deep learning techniques. CNN has a worse performance with recall and precision at 89.5% and 91.2%, respectively, whereas DNN shows some improvement with both metrics at 91.3% and 92.7%, respectively. The generic DL approach performs even better with 93.6% recall and 94.1% precision. On the other hand, the new approach performs the best with the highest recall and precision of 96.2% and 97.8%, respectively.

5. Conclusion

Finally, the proposed IoT framework based on ML models for early detection of chronic diseases using wearable sensors exhibits an extremely effective and efficient method for healthcare applications. This can be justified by the combination of structured clinical information, physiological signals, along with the implementation of an input-specific neural network model. The superiority of the proposed method becomes evident from the higher accuracy achieved for classification through higher recall, precision, lower RMSE, and significantly reduced computational time when compared to CNN, DNN, and DL models. It is clear that this framework is appropriate for accurate prediction of CKD cases and can be used for smart healthcare applications for making early decisions. Nevertheless, one of the main limitations associated with the application of the proposed framework includes its limitation by a relatively small amount of single domain data set. Moreover, several important issues related to the practical realization and real-life implementation were not considered during the research process. The following areas include data protection and security, sensors' reliability, as well as scalability problems for IoT networks. Further research will focus on the development of a model capable of predicting multiple types of chronic diseases based on larger data sets.

Reference

[1] Murumkar, Sujit. "The Role of Machine Learning in Early Detection of Chronic Diseases through Wearable Data." International Journal of Artificial Intelligence, Data Science, and Machine Learning 6.2 (2025): 172-179.

[2] Badidi, Elarbi. "Edge AI for early detection of chronic diseases and the spread of infectious diseases: opportunities, challenges, and future directions." Future Internet 15.11 (2023): 370.

[3] Husnain, Ali, et al. "A precision health initiative for chronic conditions: design and cohort study utilizing wearable technology, machine learning, and deep learning." International Journal of Advanced Engineering Technologies and Innovations 1.2 (2024): 118-139.

[4] Veernapu, Kiran. "The Role of Wearable Devices in Chronic Disease Management: A Review of Current AI and ML Applications and Future Directions." IJLRP-International Journal of Leading Research Publication 5.4 (2024).

[5] Yuan, Xichen, et al. "Epidermal wearable biosensors for monitoring biomarkers of chronic disease in sweat." Biosensors 13.3 (2023): 313.

[6] Adelusi, BAMIDELE SAMUEL, et al. "Integrating wearable sensor data with machine learning for early detection of non-communicable diseases." Journal Not Specified (2023).

[7] Adelusi, Bamidele Samuel, et al. "A machine learning-driven predictive framework for early detection and prevention of cardiovascular diseases in US healthcare systems." Engineering and Technology Journal 10.5 (2025): 4727-4751.

[8] Hosain, Md Najmul, et al. "IoT-enabled biosensors for real-time monitoring and early detection of chronic diseases." Physical activity and nutrition 28.4 (2024): 60.

[9] Wu, Chia-Tung, et al. "A precision health service for chronic diseases: development and cohort study using wearable device, machine learning, and deep learning." IEEE journal of translational engineering in health and medicine 10 (2022): 1-14.

[10] Materia, Frank T., and Joshua M. Smyth. "Acceptability and concerns about innovative wearable health sensors in persons with and without chronic disease diagnosis." Internet Interventions 35 (2024): 100702.

[11] https://www.kaggle.com/datasets/abhia1999/chronic-kidney-disease

[12] Jadoon, Asghar A., et al. "Input specific neural networks." Computational Mechanics (2026): 1-23.