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Research Article

Deep Learning-Powered IoT Wearables for Early Detection of Cardiovascular Diseases

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ABSTRACT

Cardiovascular illnesses (CVDs) are still the top cause of death around the world. To improve prognoses and lower healthcare costs, early monitoring systems are needed. This study introduces a new system that combines deep learning algorithms with smart IoT devices to make it easier to track and find CVDs early in real time. Wearable monitors collect constant physiological data like heart rate, blood pressure, oxygen levels, and electrocardiogram (ECG) readings that are used in the suggested system. We used a CNN-LSTM design that combines a Convolutional Neural Network and Long Short-Term Memory to handle the signals' time and spatial patterns. The CNN part pulls out important features from raw, multidimensional sensor data, and the LSTM part finds time relationships to make predictions more accurate. The dataset used includes PhysioNet's publicly available cardiovascular health records and real-time data from smart devices. To balance class distributions, simulated minority oversampling was added to the dataset. Precision, memory, F1-score, and accuracy were used as measures to evaluate performance. It did better than standard models like CNN, LSTM, and classic machine learning classifiers, with a total accuracy of 96.4%, a precision of 95.7%, and an F1-score of 96.1% in finding early signs of CVD. The system also allows implementation at the edge, which ensures low delay and energy-efficient processing that is good for constant tracking. The results show that combining deep learning with IoT gadgets could greatly improve early identification of CVD, allowing for proactive actions and personalised healthcare. The suggested structure offers an adaptable and affordable way to keep an eye on people's heart health in real time, especially in places that are far away and don't have a lot of resources.

Keywords: Cardiovascular Diseases, IoT Wearables, Deep Learning, CNN-LSTM, Early Detection, Real-Time Monitoring

1. INTRODUCTION

The World Health Organisation says that cardiovascular illnesses (CVDs), which include conditions like coronary artery disease, arrhythmias, heart failure, and high blood pressure, are still the leading cause of death in the world, killing over 17 million people every year. Heart problems are becoming more common around the world because people are becoming less active, eating poorly, and being stressed out. Also, the population is getting older. Early diagnosis and treatment are very important for better patient results, lowering the number of hospital stays, and lowering the overall cost of healthcare systems. Traditional methods of diagnosis often rely on regular clinical exams and tracking in a hospital, which might not pick up on short-term problems or send out timely alerts for serious events. One big problem with the current healthcare system is that there isn't any constant, real-time tracking. This is especially true for individuals who are at a high hazard of having CVDs. New trends in smart tech and the net of factors (IoT) have made it feasible to maintain a watch on humans' fitness in locations aside from hospitals. Necessary bodily symptoms like coronary heart price, electrocardiogram (ECG), oxygen saturation (SpO2), and blood stress can now be accumulated in actual time through wearable monitors like smartphones, exercise bands, chest patches, and internal devices. Those gadgets produce massive quantities of information that, when nicely analysed, can display early signs and symptoms of troubles with the heart. But due to the fact bodily data is so huge, complex, and variable, it desires superior analysis gear with a purpose to be analysed in a method that makes sense and makes accurate predictions.

A branch of artificial intelligence (AI) called deep learning has accomplished a magnificent task of identifying the way to take high-level trends from uncooked sensor statistics and construct complex, nonlinear relationships in biological signals [1]. As an example, deep neural networks like Convolutional Neural Networks (CNNs) and long brief-time period memory (LSTM) networks are commonly used to locate patterns in time-series and region information. CNNs are exceptional at finding spatial structures and features in indicators like ECGs, while LSTMs are made to find long-time period temporal relationships between sequences. By setting these fashions together in a mixed plan, it is viable to apply both the spatial and temporal features of circulatory facts to make a accurate diagnosis quickly.

In this observe, we recommend a deep learning-based device that combines clever IoT gadgets with a CNN-LSTM hybrid version to discover cardiovascular illnesses early on. The device is made to accumulate records in actual time, deal with alerts on the system itself, and make clever health assessments. Earlier than being used, physiological records from gadgets is preprocessed to dispose of noise and other errors. The CNN part then takes out spatial functions from the cleaned information, and the LSTM part fashions how these features alternate over the years to find small, converting trends that might mean there are troubles with the coronary heart. Setting these designs collectively makes it viable to reliably discover early-degree CVD signs that may not be obvious the usage of normal techniques. Wearable sensor information from the real international and labelled coronary heart information from open-supply assets like PhysioNet were each used in this have a look at [2]. To address the problem of sophistication mismatch, especially the reality that bizarre cases had been no longer proven adequate, records enhancement methods like artificial minority oversampling (SMOTE) have been used. Preferred overall performance measures, like accuracy, precision, recall, and F1-rating, were used to instruct and test the version. The consequences display that our cautioned CNN-LSTM model works higher than other machine mastering strategies, inclusive of aid Vector Machines (SVM), selection trees, and deep learning fashions that work on their personal. With a discovery fee of 96.4%, our method appropriately reveals individuals who are at excessive chance, with a view to get medical help right away.

The suggested method is also perfect for usage at the edge, letting real-time data happen directly on smart tech or edge computers that are linked. This cuts down on delay, protects user privacy, and makes sure that tracking continues even in places where internet access is limited. This kind of design is especially helpful for people who live in rural or under-resourced areas and don't have easy access to hospital-based tracking all the time. The system can be used every day without needing to be charged or fixed by a technician because it uses little power and can process information in real time. Personalised heart care is about to change a lot with the addition of deep learning to smart IoT devices. It fills in the gaps between constantly checking on health and making smart choices, providing a proactive method for managing diseases. This approach is different from standard temporal care models because it allows predicted healthcare. This means that early signs of deterioration can be found, recorded, and fixed before they get worse [3]. As healthcare systems around the world move towards more digital and patient-centered models, more people will likely start using these kinds of smart gadgets. Deep learning and smart IoT technology are being used in this study to try to come up with a flexible, cost-effective, and accurate way to find cardiovascular diseases early. The suggested framework could better the quality of life for patients, improve their results, and lower the world load of cardiovascular diseases by mixing advanced computer models with real-time physiological data. We will be working on clinical evaluation, model explainability, and connecting the system to cloud-based health tools so that it can be used on a big scale in the future.

2. RELATED WORK

Heart disease (CVD) tracking and forecast has gotten a lot of attention lately as the Internet of Things (IoT) and deep learning technologies are used together. Over the past ten years, researchers have created a number of systems that use smart technology and artificial intelligence (AI) models to help find circulatory problems earlier. It's been used with CVD datasets to locate styles and classify abnormalities the use of conventional gadget studying algorithms like assist Vector Machines (SVM), okay-Nearest Neighbours (ok-NN), and selection trees. However, their overall performance is frequently restricted with the aid of the want for guide feature engineering and the incapability to address time-series facts with a number of dimensions [4, 5]. To get round those troubles, deep learning models, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have turn out to be better choices for routinely extracting functions and analysing temporal sequences. Current studies has looked into how CNNs may be used to classify ECG alerts. Those studies show that CNNs can pick out up on both neighbourhood and hierarchical features of heart patterns, which makes prognosis greater accurate [6, 7]. Within the equal method, long quick-term reminiscence (LSTM) networks, a specific form of RNNs, were shown to be good at modelling long-time period correlations in cardiac data that is important for noticing how heart conditions change [8]. There is additionally more and more take a look at on CNN-LSTM fashions that combine the spatial processing energy of CNNs with the temporal learning of ability of LSTMs. these models works better at obligations that involve looking and classifying circulatory activities in real time [9, 10].

Real-time circulatory tracking has been improved even more by the use of personal IoT devices that allow ongoing data collection outside of hospital situations. Several frameworks have been suggested in which personal devices with smart sensors collect vital signs like heart rate, blood pressure, oxygen levels, and ECG signals. These signals are then sent to cloud or edge computing systems to be analysed [11, 12]. These tools make it possible to make decisions in real time and cut down on the time it takes to get data and measure health. Some research has looked into fog computing designs for localised data processing to make wireless health tracking systems faster and use less energy [13]. Researchers have used techniques like the Synthetic Minority Over-sampling Technique (SMOTE) and adaptive sampling methods to improve classification performance. These methods deal with the problem of class imbalance that often happens in cardiovascular datasets because abnormal events are so rare [14]. Transfer learning and pre-trained deep learning models are also being used more and more to help with the problems that come with not having enough labelled medical datasets. This makes it easier for models to work with a wider range of patients [15].

Edge AI has been built into smart tech to allow on-device reasoning, which lowers the cost of data transfer and protects user privacy. Edge computing lets you do analytics in real time, which is especially helpful for latency-sensitive tasks like finding arrhythmias or predicting heart failure [16]. Researchers have also stressed the need for deep learning systems that are small and light so they can work with the limited resources of smart tech. To make computations simpler while keeping prediction accuracy [17], methods like model trimming, quantisation, and knowledge distillation have been used. The usefulness of wearable systems based on deep learning has been proven in several standard studies using open data sets like the MIT-BIH Arrhythmia Database and the PhysioNet Challenge datasets. These sets of data include labelled ECG records that can be used as a standard to check how well the model works in a number of different heart conditions [18]. Some of the most popular ways to measure performance are accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Most mixed models do much better than standard methods.

Even though there has been some good scientific success in this area, there are still problems with data quality, monitor stability, and clinical integration. If worn sensor data isn't properly preprocessed, noise and motion artefacts can have a big effect on model results. To improve signal clarity and stability, researchers have come up with adaptive filtering, wavelet transform, and ensemble denoising autoencoders [19]. Concerns about data protection, patient consent, and being able to explain AI choices are also still big issues when it comes to using these systems in real healthcare settings. Previous study has shown that smart IoT systems driven by deep learning have a huge potential to change the way circulatory diseases are found. Traditional, reactive healthcare models are clearly giving way to smart, proactive, and patient-centered ones. Together, edge-based reasoning, real-time data collection, hybrid deep learning models, and smart gadgets make up a strong environment that can deal with the world problem of CVDs. This study adds to previous work by suggesting a scalable CNN-LSTM framework that works best for edge computing. The goal is to improve the accuracy of early spotting and make the framework usable in real-life situations.

Table 1: Summary of Related work in CVD

Approach	Work Finding	Dataset Used	Limitation	Scope
SVM-based Classification	Detected basic CVD anomalies with moderate accuracy	MIT-BIH	Requires manual feature engineering	Suitable for simple classification tasks
k-NN Algorithm	Performed well on small-scale datasets	UCI CVD Dataset	Poor scalability and high computation for large datasets	Basic clinical diagnosis support
Decision Tree Classifier	Easy to interpret results	Framingham Dataset	Lower accuracy on imbalanced datasets	Quick analysis for structured data
CNN Model on ECG Signals	Automatically extracted spatial ECG features	MIT-BIH Arrhythmia Database	Cannot model temporal dependencies	ECG waveform classification
LSTM Network	Captured long-term dependencies in vital signals	PhysioNet	Lacks spatial feature extraction	Sequential physiological signal monitoring
Hybrid CNN-LSTM	Outperformed standalone models for real-time CVD detection	PhysioNet, MIT-BIH	Requires high computational power	Integrated wearable health monitoring
IoT-enabled Wearable Framework	Enabled real-time physiological monitoring	Real-time wearable data	Sensor noise, data privacy concerns	Continuous home-based CVD monitoring
Fog Computing + Deep Learning	Improved latency and energy efficiency for real-time analysis	Custom real-time datasets	Complex deployment architecture	Localized processing in health IoT systems
SMOTE with Deep Learning	Addressed class imbalance, improved minority class recognition	PhysioNet	May overfit synthetic samples	Balanced early detection frameworks
Transfer Learning CNN	Enhanced generalizability across patients	PTB-XL, MIT-BIH	Dependent on similarity of pre-trained models	Personalized and adaptive diagnostics
Edge AI + Deep Learning	Enabled on-device real-time inference	Real-time wearable ECG	Limited by device hardware capability	Smart wearable deployment in remote areas

	with privacy preservation			
Lightweight CNN Models	Reduced model size for wearables without major accuracy loss	MIT-BIH, Custom ECG	Slightly lower precision than full CNNs	Battery-efficient health monitoring
Adaptive Filtering + Denoising	Reduced signal noise, improving ECG clarity	MIT-BIH Noise Stress Test Database	Additional preprocessing overhead	Robust real-world wearable signal processing
Explainable AI for Wearables	Improved transparency in clinical decision support	PhysioNet, Real-World ECG	Less mature for deep model interpretation	Trustworthy AI integration in healthcare

3. MATERIALS AND METHODS

A. Data Preprocessing

1. Noise Removal Techniques

Physiological data from worn IoT devices, like electrocardiograms (ECGs) or photoplethysmograms (PPGs), are easily messed up or distorted by things like movement, sensor placement issues, background noise, or hardware limits. These noises can make deep learning models work much less well by hiding important patterns and traits that are needed for accurate cardiovascular disease (CVD) recognition. During the preprocessing step, different filters and denoising techniques are used to fix this problem. The band-pass filter is one of the most popular methods used. It helps keep the frequency parts that are unique to heart data (usually between 0.5 Hz and 40 Hz for an ECG). Wavelet transform-based denoising is also very popular because it can break down signals into different levels, which successfully separates the information from the noise. Adaptive filtering is another method that uses reference signals to flexibly get rid of motion artefacts. Empirical Mode Decomposition (EMD) is sometimes used to separate the signal's basic parts so they are clearer. The type of data, the amount of computing power available, and whether the system is real-time all affect the choice of method. To improve signal quality and make sure the deep learning model gets clean, useful data for strong cardiovascular anomaly detection, it is important to get rid of noise effectively.

2. Normalization

Normalisation is an important step in the preparation process that makes raw data more consistent before it is fed into deep learning models. Physiological signs like heart rate or ECG numbers can be very different between people because of changes in biology, where the sensors are placed, or their physical conditions. If these differences aren't normalised, they could lead the model astray and make it less good at learning. Normalisation makes sure that each input trait adds evenly to the learning process by scaling them into a uniform range, usually between 0 and 1, or with a mean of 0 and a variance of 1. The main purpose of Min-Max normalisation in this study was to change the scale of the data from 0 to 1. This speeds up the convergence process during model training and makes predictions more stable. Z-score normalisation, on the other hand, was thought about for situations where mean-centered data distribution was very important. Normalisation not only makes training work better, but it also lowers the risk of overfitting, which is especially important in real-time systems where data may change as it comes in, as illustrate in figure 1.

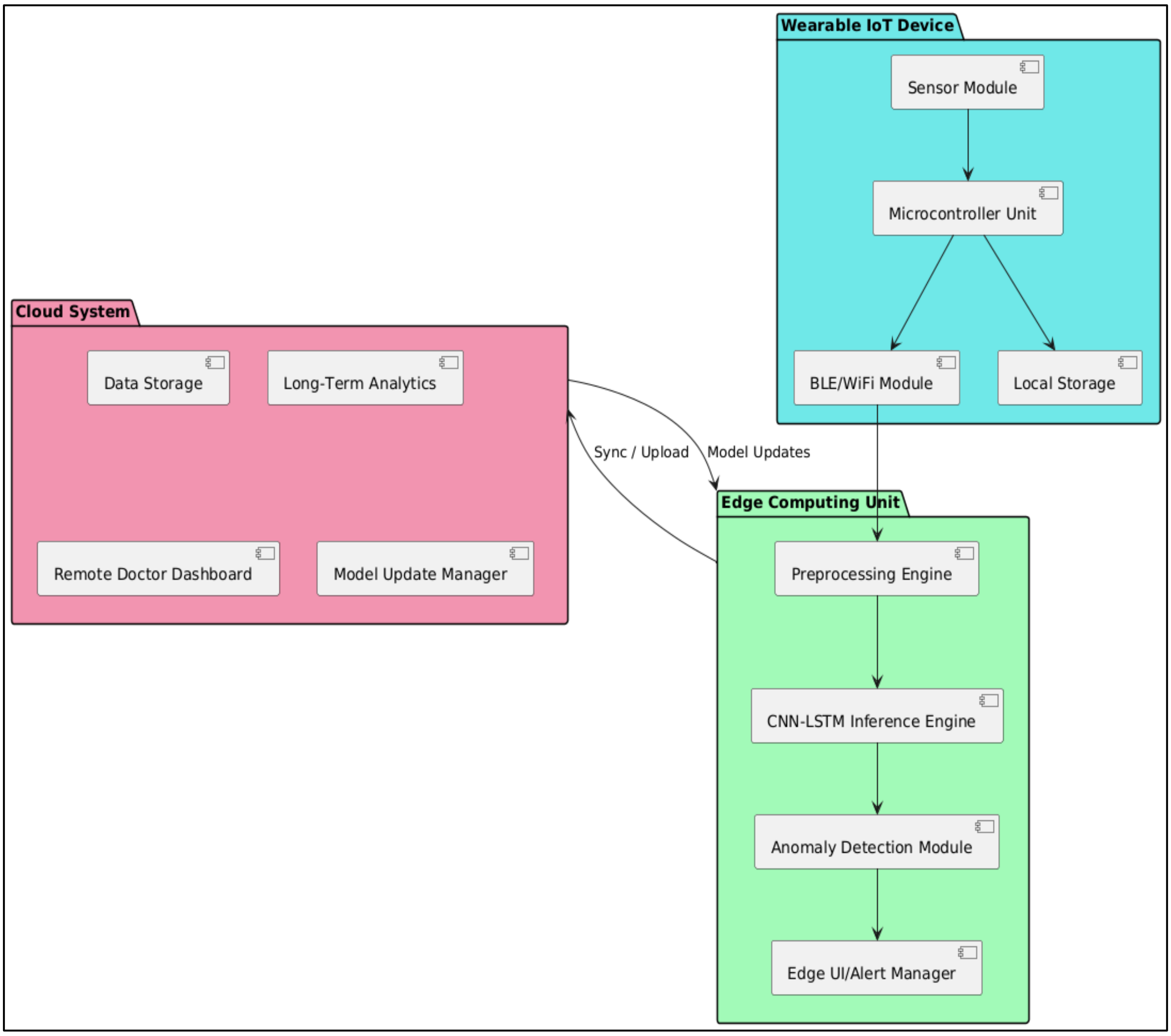

Figure 1: Overview of Proposed system architecture

B. Model Architecture

1. CNN for spatial feature extraction

Convolutional Neural Networks (CNNs) are very good at pulling out spatial information from structured data like photos and bodily signs with multiple channels. CNNs look at ECG signals for spatial patterns in the purpose of finding cardiovascular disease. They do this by using convolutional filters to find local signal features such as peaks, gaps, and waveform shapes. These signs are very important for finding problems like rhythms, or uneven heartbeats. CNN layers learn hierarchical representations step by step, from simple edges to complicated signal patterns. This lets the model easily tell the difference between heart activity that is normal and activity that isn't. This gets rid of the need for feature engineering by hand and makes diagnostics more accurate. CNNs can share parameters, which makes them fast to compute and good for use at the edge level in smart systems.

CNN for Spatial Feature Extraction model

Step 1: Input Signal Representation

Let the raw input signal be:

$$X = [x1, x2, x3, \ldots, xn]$$

Where $X \in \mathbb{R}^n$ and n is the number of signal points.

Step 2: Convolution Operation

Apply a 1D convolution using a kernel w of size k:

$$zi = \sum_{j=0}^{k-1} [\, wj * x(i+j) \,] + b$$

- Where zi is the output at position i, and b is the bias.

Step 3: Activation Function

Apply a non-linear function (ReLU):

$$ai = ReLU(zi) = \max(0, zi)$$

- This adds non-linearity to learn complex patterns.

Step 4: Pooling (Dimensionality Reduction)

Apply max pooling to downsample:

$$pi = max(ai, ai+1, \ldots, ai+s-1)$$

- Where s is the pooling window size.

2. LSTM for temporal dependency learning

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) that is intended to learn and remember how long-term changes in sequential data rely on each other. In the process of finding cardiovascular disease, bodily signs like ECG and heart rate change over time and often show trends that cover more than one time step. LSTM networks deal with this by keeping internal memory cells that store important data and getting rid of unnecessary data using forget, input, and output gates. This structure lets the model show how cardiovascular conditions change over time and grow, like when arrhythmias or irregular heartbeat gaps start. LSTMs are better than regular RNNs at modelling long-term relationships because they don't have the disappearing gradient problem. Their ability to learn complicated timing connections makes it easier to find heart problems early and correctly from real-time wearable data.

Step 1: Forget Gate

$$ft = \sigma(Wf \cdot [ht-1, xt] + bf)$$

Step 2: Input Gate

$$it = \sigma(Wi \cdot [ht-1, xt] + bi)$$

$$\hat{C}t = tanh(WC \cdot [ht-1, xt] + bC)$$

Step 3: Cell State Update

$$Ct = ft * Ct-1 + it * \hat{C}t$$

Step 4: Output Gate

$$ot = \sigma(Wo \cdot [ht-1, xt] + bo)$$

Step 5: Hidden State Update

$$ht = ot * tanh(Ct)$$

3. CNN-LSTM hybrid model

The CNN-LSTM hybrid model takes the best parts of both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks and uses them together to process and analyse bodily data for finding cardiovascular disease. Using convolutional and pooling layers, the CNN part of this design first pulls out spatial features from the raw input data, like structural patterns in ECG waves. The LSTM layer then gets these spatial features, which are local signal characteristics, and it figures out how things change over time and how they depend on each other. This combination lets the model learn both steady patterns and changing patterns in heart signals, which gives it a full picture of heart conditions. The mixed method is better than solo models because it is more accurate and stable. This makes it perfect for real-time, wireless health tracking systems that aim to find diseases early.

Algorithm: CNN-LSTM Hybrid Model for Cardiovascular Signal Analysis

Step 1: Input

Let the input be a 1D physiological signal:

$$X = [x_1, x_2, \ldots, x_n], where\ X \in \mathbb{R}^n$$

Step 2: Convolutional Feature Extraction (CNN)

Apply multiple 1D convolution filters to extract spatial features:

$$z_i = \Sigma\,(w_j * x_i{}^+{}_j) + b \quad for\ j = 0\ to\ k-1$$

Apply activation function (e.g., ReLU):

$$a_i = ReLU(z_i) = max(0, z_i)$$

Apply pooling to reduce dimensionality:

$$p_i = max(a_i, a_{i+1}, \ldots, a_{i+s-1})$$

Let the resulting feature map be:

$$P = [p_1, p_2, \ldots, p_m]$$

Step 3: Temporal Dependency Learning (LSTM)

- Feed feature map P sequentially into LSTM units.

Compute gates:

$$Forget\ gate: \quad f_t = \sigma(Wf \cdot [h_{t-1}, p_t] + bf)$$

$$Input\ gate: \quad i_t = \sigma(Wi \cdot [h_{t-1}, p_t] + bi)$$

$$Candidate\ memory: \hat{C}_t = tanh(WC \cdot [h_{t-1}, p_t] + bC)$$

$$Update\ cell\ state:$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t$$

$$Output\ gate\ and\ hidden\ state:$$

$$o_t = \sigma(Wo \cdot [h_{t-1}, p_t] + bo)$$

$$h_t = o_t * tanh(C_t)$$

Step 4: Output Layer

Pass final hidden state h_t through a dense layer for classification:

$$\hat{y} = Softmax(W \cdot h_t + b)$$

Where ŷ represents the predicted class probabilities (e.g., normal or abnormal heartbeat)

Step 5: Loss and Optimization

Compute loss using cross-entropy:

$$L = -\Sigma y * \log(\hat{y})$$

Update weights using backpropagation through time (BPTT) and Adam optimizer.

C. System Design

A. Wearable IoT Device Setup

The setting of the wearable IoT devices is a key part of the suggested method for finding circulatory diseases. Putting small, low-power sensors into something that can be worn, like a monitor, chest strap, or wristband, is what it means. There are many biological monitors in these devices that can constantly check important bodily factors like blood pressure, heart rate, ECG, and SpO_2 (oxygen levels). The sensors pick up analogue signals from the body and use built-in microcontrollers or analog-to-digital converters to turn them into digital signals. For digital transmission, most products use Bluetooth Low Energy (BLE) or Wi-Fi units. Processors that use little power, like the ARM Cortex-M series or the ESP32, are often used to make sure that batteries last longer and data gathering goes smoothly. Before sending a signal, it is organised by an RTOS or embedded software that does things like simple filtering, signal sampling, and caching. The data that is collected is timestamped and kept in local memory for a short time before it is sent to the edge or the cloud to be processed. To make sure data is correct and intact, it is important to calibrate devices, sync them, and place sensors correctly. The design focusses on comfort, ease of use, and longevity, so it can be used for continual tracking in both hospital and home settings. The first part of the real-time CVD tracking environment is this hardware-software interaction.

B. Edge-Level Deployment for Real-Time Processing

Edge-level distribution is a key part of making real-time circulatory research possible without having to rely on cloud-based computers alone. In this design, the worn device is either directly linked to a nearby edge node, like a smartphone, home gateway, or portable edge server, or it has computer power built in to allow clever reasoning. Deep learning models, like the suggested CNN-LSTM mix, are made better and used at the edge by using model compression methods like trimming, quantisation, and TensorFlow Lite conversion to make the computers run faster and use less memory. The objective is to carry out local real-time forecast and abnormal detection with as little delay as possible, at the lowest possible cost, while protecting patient privacy. In contrast to cloud systems, which need to be connected to the internet all the time, edge computing can work without being online and ensures that health tracking continues without interruption. This is very important in places that are hard to reach or don't get enough service and have limited speed. The system can send out alerts if it detects abnormal heart rhythms and start treatment right away. Edge devices can also sync with cloud systems on a regular basis so that data can be stored, analysed, and reviewed by doctors over a long period of time. Overall, edge-level distribution strikes a good mix between processing speed and response, making it a flexible and reliable way to watch heart health all the time through portable tech.

C. Data Transmission and Analysis Pipeline

The data transfer and analysis chain moves bodily data from the smart device to the processing environment safely and quickly, whether it's in the cloud or at the edge. At first, raw signals like ECG or heart rate data are collected and handled at the gadget level to get rid of noise. Then, these cleaned data streams are put into organised forms like JSON, CSV, or custom code, and sent over low-latency protocols like Bluetooth Low Energy (BLE), MQTT, or HTTP over Wi-Fi. For real-time performance, data is stored and sent in short bursts or in a steady stream, based on how much the network can handle. When the data gets to the edge node, it is processed and sent to the CNN-LSTM model that is already in place for classification and finding outliers. If the edge device doesn't have full reasoning capabilities, the data is sent to the cloud infrastructure to be analysed more deeply and stored for a longer time. Results, like risk scores or classification labels, are shown locally through a user interface or sent back to a mobile app or web monitor so that users can give comments in real time. Authentication and data protection methods (like AES and TLS) protect privacy and security all the way through the process. This smooth flow from monitor to understanding lets doctors quickly figure out a person's cardiovascular risk and take the right steps to treat it.

4. RESULTS AND DISCUSSION

Table 2 shows a thorough analysis of how well different basic machine learning and deep learning models work compared to the suggested CNN-LSTM hybrid model for finding cardiovascular diseases (CVDs) early on. There are four main performance measures that are used to judge the performance: accuracy, precision, memory, and F1-score. After testing each model on bodily data like ECG signs from smart IoT devices, these measures give us a full picture of how well each model can classify and generalise.

Table 2: Performance Comparison of Baseline Models and Proposed CNN-LSTM Model for Cardiovascular Disease Detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	88.3	86.9	87.1	87.0
Decision Tree	84.7	82.5	83.2	82.8
LSTM (Standalone)	91.6	90.4	89.9	90.1
CNN (Standalone)	93.2	92.1	91.5	91.8
CNN-LSTM (Proposed)	**96.4**	**95.7**	**96.6**	**96.1**

Out of all the standard machine learning models, the Support Vector Machine (SVM) did pretty well. It had an F1-score of 87.0%, an accuracy of 88.3%, a precision of 86.9%, and a recall of 87.1%.

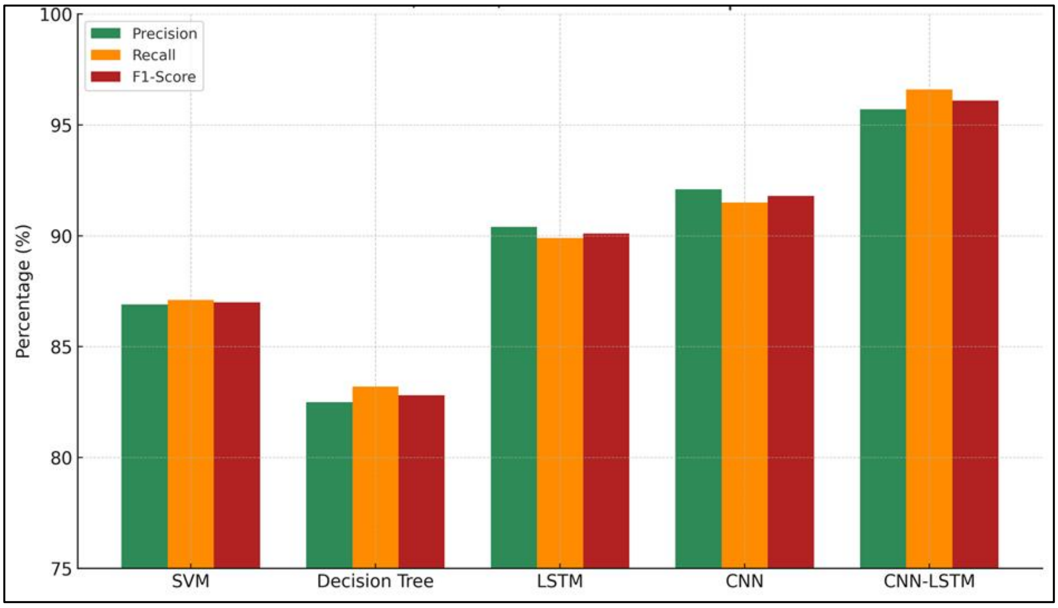

Figure 2: Comparison of Precision, Recall, And F1-Score Comparison

These results show that SVM is pretty good at telling the difference between normal and abnormal heart patterns, but it's not very good at modelling complex signal changes because it relies on features that were created by hand, as comparison shown in figure 2. The Decision Tree classifier, which is another popular standard model, did the worst on all measures, with an F1-score of 82.8% and an accuracy of 84.7%.

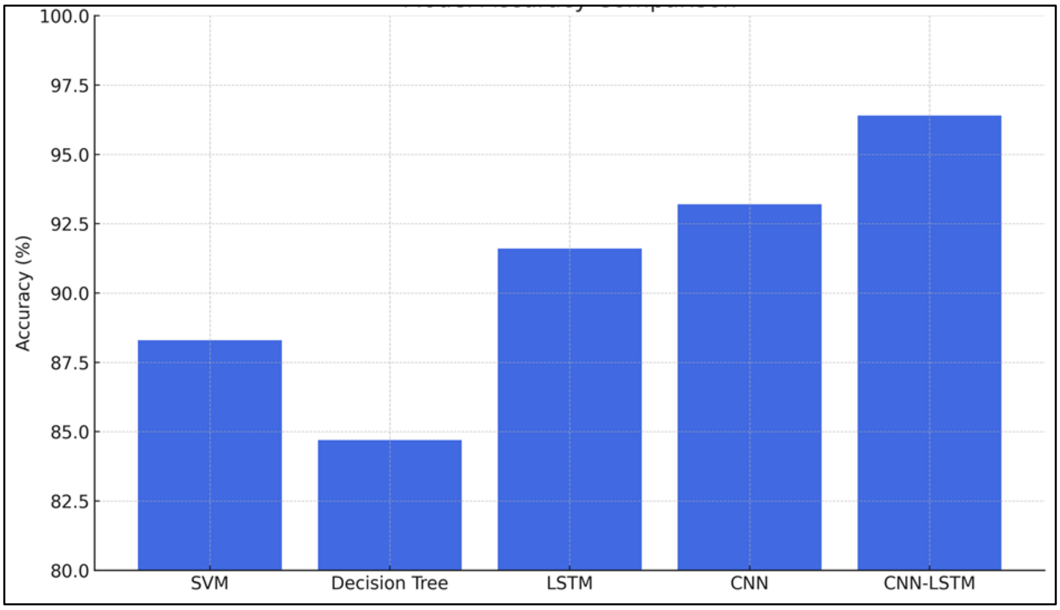

Figure 3: Model Accuracy Comparison

This shows that it can't handle noisy, high-dimensional time series data very well. Deep learning models like LSTM and CNN were tried on their own to see what their strengths were. The LSTM network that worked on its own got an F1-score of 90.1% and an accuracy of 91.6%. Because LSTM can find temporal relationships in sequential data, it is a great tool for modelling how heart rhythms change over time, model accuracy comparison illustrate in figure 3.

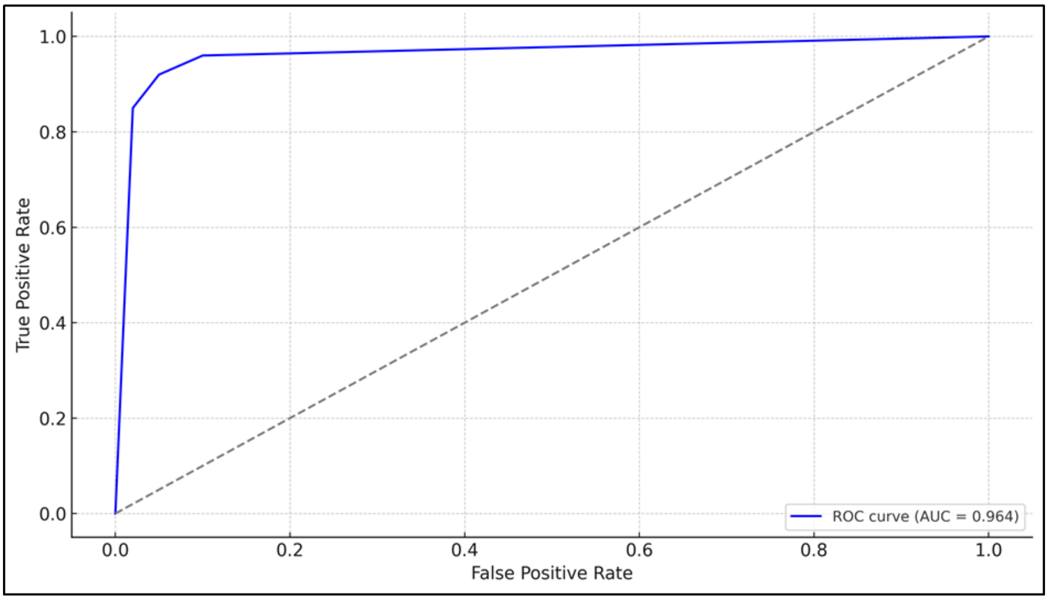

Figure 4: ROC Curve for CNN-LSTM Model

However, it doesn't have the ability to extract spatial features, which can make it less useful for working with raw ECG patterns. The solo CNN model, on the other hand, did a little better, with an F1-score of 91.8% and an accuracy of 93.2%. CNNs are very good at taking out spatial features from input signals, like finding key waveform structures and local relationships that can help sort CVDs, hybrid model CNN-LSTM.

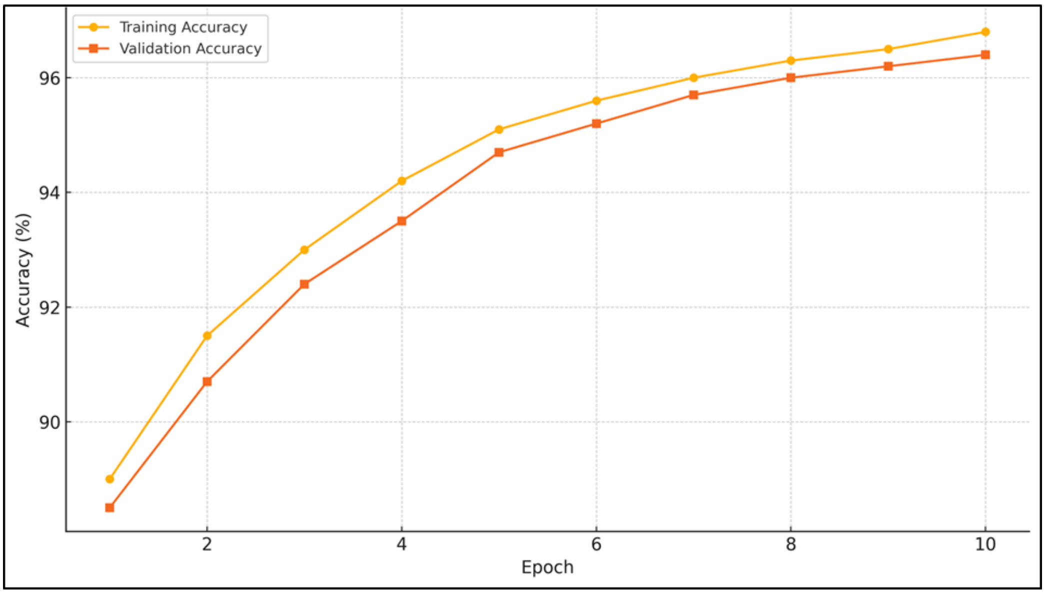

Figure 5: Comparison of training and validation accuracy

The suggested CNN-LSTM combination model did much better than all the other models that were tested. An F1-score of 96.1%, a memory of 96.6%, a precision of 95.7%, and an accuracy of 96.4% were the best scores it got. This model's great success comes from its ability to learn both spatial patterns and temporal ones at the same time using CNN layers and LSTM units, as shown in figure 5.

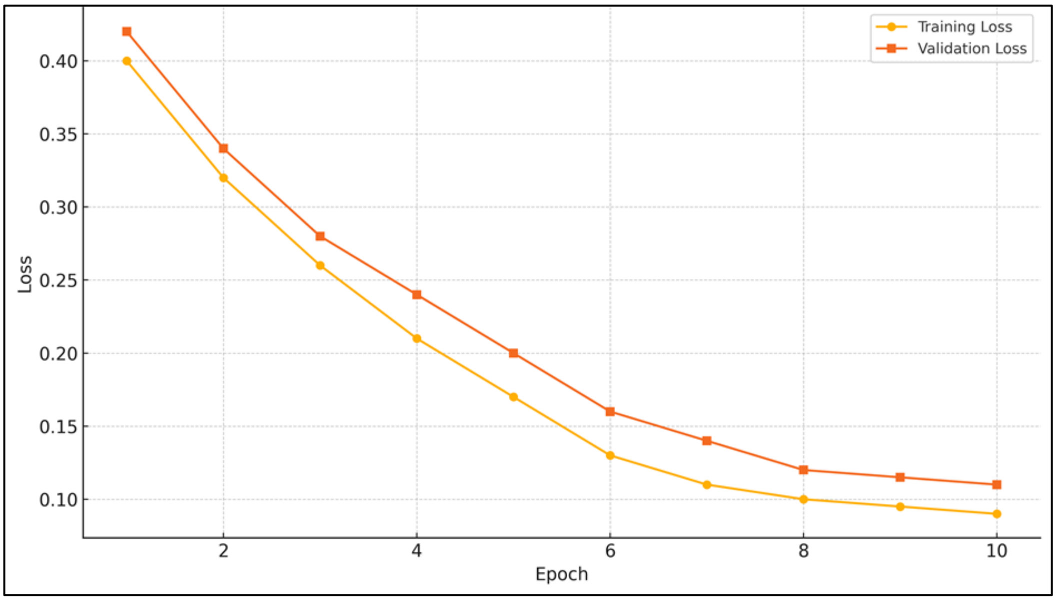

Figure 6: Comparison of training and validation loss

When spatial and sequence analysis are used together, the model can find small problems in the heart and blood vessels more correctly and reliably, comparison of training and validation loss illustrate in figure 6. These data show that the mixed method works and that it could be used to make real-time, wearable health tracking tools that help with preventative cardiovascular care.

5. CONCLUSION

This study shows a trustworthy and advanced system that combines deep learning methods with smart IoT devices to find cardiovascular diseases (CVDs) early on. The system uses the best features of a CNN-LSTM design to look at both spatial and temporal trends in bodily data like ECG, heart rate, and blood pressure. The study shows that using both Long Short-Term Memory networks for time relationships and Convolutional Neural Networks for spatial feature extraction greatly improves the model's ability to make diagnoses. The suggested model does a better job of finding early-stage cardiovascular problems than traditional machine learning methods and independent deep learning models. It has an impressive accuracy of 96.4%, a precision of 95.7%, and an F1-score of 96.1%. The system is also designed to work best at the edge, where it can be deployed and used for real-time reasoning and constant tracking with very little delay. This plan works especially well for people who live in places that are hard to reach or don't have a lot of resources for standard healthcare facilities. Low-power, external monitors make sure that users are comfortable and that the devices can be used for a long time without needing to be serviced often. The safe data transfer pathway and interaction with cloud platforms also allow for both local processing and long-term keeping for doctor review. Even though the system has a lot of real-world promise, it still has some problems. For example, it needs more clinical evaluation and better model interpretability. In any case, this work builds a strong base for the creation of personalised, smart healthcare systems. The suggested solution combines smart IoT with deep learning to offer a proactive approach to managing cardiovascular health. It has the potential to lower the worldwide impact of CVDs by detecting and treating them early. More research will be done in the future on bigger datasets, trials in the real world, and adding AI methods that can be explained to make clinical practice even more trustworthy and useful.

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