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Article

IoT-Enabled Health Monitoring System with Vision Transformer-Based ECG Anomaly Detection

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Abstract: Early cardiovascular disease detection depends highly on real-time health monitoring because of its increasing prevalence in society. Hospital-based monitoring through periodic checkups delays disease detection causing higher death rates among patients. Existing IoT-based systems capable of tracking vital signs including heart rate and body temperature and oxygen saturation levels still need real-time anomaly alerting features and automated emergency notifications as well as AI suggestion capabilities. Deep learning models that use conventional methods like CNNs face challenges when trying to extract useful features from ECG signals which negatively affects their classification results. The proposed solution implements a Shayan Fazeli Heartbeat Dataset from Kaggle-powered IoT-based healthcare system that utilizes Vision Transformer (ViT) for heartbeat classification. The proposed model delivers 99.995% accuracy representing superior results beyond CNN-based classification methods. The system detects abnormal heart rhythms and then immediately notifies the closest hospital and generates automatic prescription messages through mobile devices for patient self-care when body temperature becomes abnormal. Our system benefits telemedicine decision-making through IoT integration with advanced deep learning which provides better emergency response time along with superior predictive accuracy and it produces improved patient outcomes.
Keywords: NA

1. INTRODUCTION

Remote health monitoring technology serves two important functions by decreasing hospital visits and enabling early cardiovascular condition detection because of continuous patient assessment. Medical organizations presently use scheduled examinations to detect diseases but these methods lead to delayed diagnoses and elevated death rates because of delayed identification of medical issues. Through IoT-based real-time monitoring solutions health patients receive automatic continuous monitoring of vital signs including heartbeat along with body temperature and oxygen levels to initiate early treatment. This healthcare approach assists medical facilities while improving patient treatment by allowing immediate medical assistance. AI-driven diagnostic tools in remote health monitoring systems perform automated alerts to advance healthcare prevention and minimize the need for in-person patient appointments.

Health monitoring systems through IoT use intelligent sensor technology alongside real-time data transmission protocols to track vital parameters including ECG (electrocardiogram), body temperature as well as SpO_2 (oxygen saturation levels).

The AD8232 ECG sensor detects heart signals to identify multiple heartbeat patterns as well as arrhythmias and tachycardia and bradycardia cardiac abnormalities. IoT-based ECG systems perform automated heartbeat classification through deep learning models while providing remote continuous ECG tracking to patients who need to stay at home.

Real-time body temperature measurement of patients becomes possible through the use of non-contact infrared sensors such as MLX90614. System-generated medical recommendations appear on mobile devices for patients in case of anomalies like fever or hypothermia to expedite necessary self-care responses.

A monitoring system for SpO_2 enables vital assessment of blood oxygen levels that remains essential for medical patients with heart conditions including those affected by COVID-19 and those diagnosed with breathing difficulties or other respiratory disorders. MAX30100 sensors measure SpO_2 levels and heart rate through infrared light absorption to discover hypoxia which becomes deadly for patients who do not receive proper treatment.

Teams should use IoT-enabled systems with MQTT communication protocols to transmit non-stop patient data into the cloud and generate immediate emergency alerts based on real-time anomaly detection. Such a system represents a vital method to improve preventive care while minimizing hospital visits through early diagnosis and prompt medical care.

This study presents an IoT-driven real-time health monitoring system that enhances early detection and response to critical health conditions. The key contributions of our work include:

- IoT System for Continuous Monitoring: The proposed system integrates ECG, SpO_2, and temperature sensors to enable real-time tracking of vital signs, reducing dependence on periodic hospital visits.
- ViT-Based Heartbeat Classification: By leveraging Vision Transformer (ViT) with self-attention mechanisms, our model achieves 99.995% accuracy in ECG classification using the Shayan Fazeli Heartbeat Dataset, significantly outperforming CNN-based approaches.
- Automated Hospital Alerts for Abnormal Heartbeats: Upon detecting arrhythmias or other critical heart conditions, the system automatically notifies nearby hospitals, ensuring faster medical intervention.
- System-Generated Prescription Messages for Temperature Anomalies: When abnormal body temperature is detected, the system automatically sends medical recommendations to the patient's mobile, promoting immediate self-care and preventive action.

By combining IoT, deep learning, and real-time decision-making, this work advances automated telemedicine solutions, improving emergency response times and patient outcomes.

2. LITERATURE REVIEW

Analysis of IoT devices and sensors for remote health monitoring appears frequently in existing literature [14,15,16,17,19]. The sensors operate by gathering physiological information for real-time health monitoring purposes as well as disease identification procedures. The use of deep learning models covers a vast spectrum of remote health monitoring applications [20,21]. The combination of convolutional neural networks produces significant improvements when doctors use annotations to identify various health problems through physiological data analysis [22,23]. Research has delivered attention-based deep learning models which enhance the ability to classify health issues effectively [24]. Researchers have developed deep learning methodologies for IoT device-based remote health monitoring together with sensor systems [25,26]. A body of research examines deep learning model structures while examining their abilities to monitor health conditions. Remote health monitoring represents a promising solution which offers enhanced patient care benefits at reduced healthcare expenses. Medical institutions obtain physiological data through their systems to detect health problems in patients while providing instant updates to healthcare providers about their patients' conditions. Modern medicine is widely using autonomous devices and IoT principles to achieve remote health monitoring services which let users track their physiological signs autonomously. This paper demonstrates remote health monitoring through IoT devices including the MAX30100 and AD8232 ECG sensor module along with the MLX90614 non-contact infrared body temperature sensor. These healthcare devices measure patient physiology in home clinical environments and transmit these readings to remote servers for digital analysis.

Analysis using deep learning models alongside simple thresholding techniques detects patterns that indicate various health problems including five arrhythmia types alongside fever and healthy states from collected data.Multiple benefits distinguish remote health monitoring from standard hospital-based healthcare systems. Through remote care patients receive ongoing medical support inside their houses minimizng both hospital trips and hospital-acquired infections. Remote health monitoring solutions alert healthcare providers to potential health issues before they become severe thereby helping both patients and their treatment outcomes. The implementation of remote health monitoring decreased healthcare expenses because it helps hospitals reserve resources better and decreases traditional patient hospital visits. Numerous research studies investigate heart disease diagnosis methods and healthcare predictive models. Researchers Tiwari and others created the Smart Cardiovascular Disease Detection System (SCDDS) which combines Internet of Things sensors within wearable technology to detect heart disease before its major onset. Through their hybrid architecture of Convolutional Neural Networks (ConvNet) and ConvNet-LSTM they deliver 98% accuracy for automatic atrial fibrillation heartbeat detection enabled by cloud-based deep learning infrastructure. Chadiya et al. [28]

designed predictive models in healthcare using hybrid combinations between human intelligence and machine systems.

The researchers applied physician expertise along with validated data sources to forecast the progression of Multiple Sclerosis (MS). The hybrid approach demonstrated superior performance than traditional approaches while demonstrating how human and artificial intelligence jointly enhance machine learning models for better individualized clinical decisions. Botros et al. [29] created a duo of models with CNN for electrocardiogram signal heart failure detection and also designed a further version adding SVM as the final layer.Model-based testing delivered outstanding detection results for HF with accuracy exceeding 99% along with sensitivity or specificity values reaching 99%.s to receive continuous care in the comfort of their homes, reducing the need for hospital visits and minimizing the risk of hospital-acquired infections. Remote health monitoring can also facilitate the early detection of health issues, enabling timely intervention and improving patient outcomes. Additionally, remote health monitoring can reduce healthcare costs by minimizing hospital visits and enabling more efficient use of healthcare resources. Several related works have explored different aspects of heart disease detection and predictive modeling in healthcare. Tiwari et al. [27] developed the Smart Cardiovascular Disease Detection System (SCDDS), which integrates IoT sensors in a wearable device for early detection of heart disease. Their ensemble architecture, combining Convolutional Neural Networks (ConvNet) and ConvNet-LSTM, achieves a high accuracy of 98% in automatically detecting atrial fibrillation heartbeats through cloud-based deep learning architecture. Chadiya et al. [28] proposed a hybrid human-machine intelligence approach for creating predictive models in healthcare. By incorporating the expertise and reasoning of expert physicians and using quality-approved data, their study focused on predicting the course of Multiple Sclerosis (MS).

The hybrid approach, which outperformed conventional methods, highlights the potential of integrating human and artificial intelligence to improve machine learning models and facilitate personalized clinical decision-making. Botros et al. [29] introduced two models, a CNN and an extended version with a Support Vector Machine (SVM) layer, for automatic detection of heart failure from electrocardiogram signals. These models achieved exceptional performance with an accuracy, sensitivity, and specificity of over 99% in detecting HF. The proposed system provides trusted health data to doctors while operating through portable equipment to supervise patients in real time.Research indicates deep learning together with IoT represents promising advances within healthcare technology. Hammad et al. [32] created a system for IoT arrhythmia identification through the combination of ConvLSTM and CNN approaches. Their approach transforms ECG signals into 2D images for subsequent classification through their proposed modeling systems that solve overfitting and manage ECG signal processing from multiple leads. The researcher applied their models to MITBIH, PhysioNet 2016, and PhysioNet 2018 databases through model evaluations leading to overall accuracies of 0.97, 0.98, 0.94, and 0.91 respectively.

Using bidirectional long-short-term memory (Bi-LSTM) Nancy et al. [33] developed a system to monitor heart disease risk in patients. The developed system demonstrated a 0.98 accuracy rate along with 0.989 precision and 0.988 sensitivity and 0.988 specificity while earning an F-measure of 0.9886 to surpass current intelligent heart condition prediction methods. The research demonstrates how disease prediction accuracy coupled with prompt detection leads to improved risk assessment for preventive healthcare intervention. Smart healthcare opportunities emerge from bringing together IoT with deep learning technologies to advance both disease prediction capabilities and patient health outcomes. Haqet al. [34] demonstrated a successful approach to brain tumor identification through deep learning methods. Researchers deployed an advanced CNN structural model to classify brain tumors through brain magnetic resonance imaging data. The model received an enhancement in its classification effectiveness through integration of dataaugmentation and transfer learning methods. The proposed model demonstrated superior performance over baseline models through high diagnostic accuracy which suggests it presents strong potential for IoT healthcare procedures focused on brain cancer detection. The field of health issue classification uses increasing amounts of deep learning models to extract vital features automatically from basic input data [35,36]. CVNNs provide exceptional results in image-based classification alongside RNNs which excel at processing sequence-based data according to research in [37].

3. METHODOLOGY

The proposed IoT-based health monitoring system uses several biomedical sensors to track real-time physiological parameters which enables continuous patient observation together with prompt anomaly alerts and quick emergency support.

3.1 Sensors Used

- MAX30100 – Heart Rate & SpO_2 Sensor

  The MAX30100 serves as an optical biosensor which determines heart rate and blood oxygen saturation level (SpO_2) through infrared and red light absorption operations.

  By employing photoplethysmography (PPG) as its operating principle the system can measure both pulse rate and oxygen levels through blood volume changes that affect light absorption precision. The device operates using minimal power which allows it to perform real-time monitoring tasks in both wearable and IoT systems.

- AD8232 ECG Sensor – Heartbeat Classification

  ANalog front-end (AFE) module AD8232 exists for the acquisition of Electrocardiogram signals.

  This device identifies heart electrical signals to automatically classify heartbeat waves between normal and irregular patterns.

  A clean ECG signal emerges from the noise reduction process through the sensor system before being used for deep learning-based classification via the ViT model.

  The sensor display adequate power efficiency and compact design features that enable its operation in portable ECG monitoring systems.

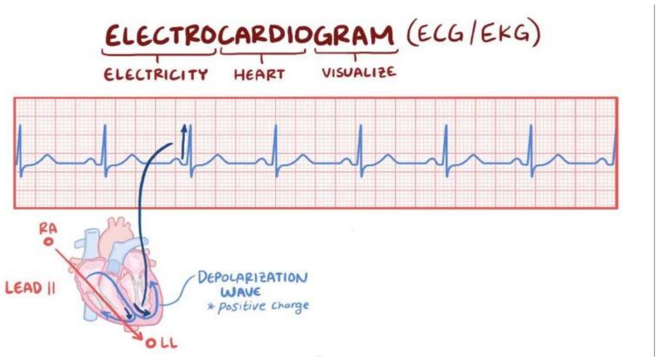

Figure 1 ECG pattern

- MLX90614 – Non-Contact Temperature Sensor

  As an infrared device the MLX90614 operates through contactless body temperature evaluation.

  The sensor achieves ±0.2°C of accuracy for real-time fever detection purposes.

  Remote sensing functions enable this sensor to work perfectly in telemedicine applications along with non-contact patient monitoring systems.

  Data Transmission and Communication

A real-time data acquisition system with processing and anomaly detection requires the MQTT (Message Queuing Telemetry Transport) protocol as its wireless data transmission method.

- MQTT Protocol for Cloud-Based IoT Communication

  The lightweight MQTT protocol works specifically with IoT applications to establish reliable data transfer between sensors and cloud-based servers through its low-bandwidth approach.

  The system transmits sensor data (ECG, SpO_2, temperature) to a cloud database in real-time, enabling remote access for hospitals and healthcare providers.

  An abnormal heartbeat occurrence sets off an automatic hospital notification system which streams alerts to the closest medical establishment.

  When body temperature exceeds normal levels the system triggers automatic immediate medical advice delivery to the patient through mobile messages.

The system integrates biomedically operated sensors alongside deep learning functionality and IoT data transmission methods to execute continuous patient healthcare monitoring remotely and better detect medical issues early and initiate quick emergency responses for future healthcare solutions.

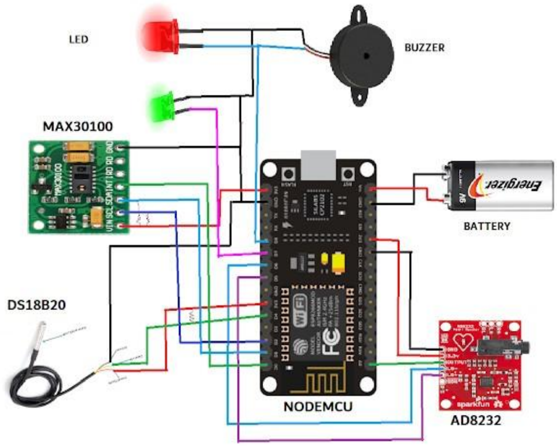

Figure 2Iot Configuration with essential sensors

3.2 Data Collection & Preprocessing

A. Dataset

The dataset comprises:

ECG Signals consist of a mixture between MIT-BIH Arrhythmia Dataset data and real-time ECG data gathered by using the AD8232 ECG sensor.

The data measurements originating from the MAX30100 sensor include levels of SpO_2 and Heart Rate.

The body temperature data was acquired through the MLX90614 non-contact infrared temperature sensor.

The real-time sensor measurements align with the MIT-BIH dataset for maintaining equivalent conditions throughout all classification operations.

B. Noise Removal

The signal quality improvement requires application of a bandpass filter that operates between 0.5 Hz – 50 Hz on ECG signals. The filtering process consists of:

The signal data contains baseline wander noise which is removed through the application of a high-pass Butterworth filter with a cutoff frequency of 0.5 Hz.

High-frequency noise elimination (e.g., muscle artifacts) via a low-pass Butterworth filter (cutoff = 50 Hz).

C. Feature Extraction

Through Wavelet Transform (WT) ECG signals undergo decomposition to different frequency bands which produces better identification of abnormalities.

The data needs normalization through applicable techniques to achieve uniform representation. To guarantee sensor reading stability across different measurements the method utilizes min-max scaling which creates value ranges from 0 to 1.

3.3 Vision Transformer (ViT) for ECG-Based Heartbeat Classification

A. Motivation for Using Vision Transformer (ViT)

Traditional convolutional neural networks (CNNs) rely on local feature extraction and struggle to capture long-range dependencies in ECG signals. Recurrent models (e.g., LSTMs) are computationally expensive and have difficulty handling complex variations in heartbeat morphology. To address these challenges, we leverage the **Vision Transformer (ViT)**, which applies **self-attention mechanisms** to learn global dependencies in ECG signals, making it highly effective for heartbeat classification.

B. ECG Signal Preprocessing and Image Representation

The dataset consists of ECG waveforms stored in **CSV format**, requiring transformation into a suitable format for ViT. The preprocessing steps are as follows:

1. **Noise Filtering:**
    - A **bandpass filter (0.5–50 Hz)** removes baseline wander and high-frequency noise.
    - The filtered signal is normalized as:

$$x_n(t) = \frac{x(t) - \mu}{\sigma}$$

    - where μ and σ are the mean and standard deviation of the signal.
2. **Segmentation & Image Conversion:**

    Each ECG segment (heartbeat) is extracted and transformed into a **2D representation** using:
    - **Continuous Wavelet Transform (CWT)**: Produces a time-frequency spectrogram.
    - **Gramian Angular Fields (GAF)**: Converts ECG time-series data into a matrix capturing temporal dependencies.
3. **Image Resizing & Augmentation:**
    - All ECG images are resized to **224×224 pixels** to match the ViT input dimensions.
    - **Data Augmentation** includes **contrast adjustment, rotation, and flipping** to improve generalization.

C. Vision Transformer (ViT) Architecture for ECG Classification

The ViT model processes the ECG images as follows:

1. Patch Embedding Layer:
    - The ECG image is divided into 16×16 non-overlapping patches.
    - Each patch is flattened and projected into a D-dimensional embedding space:

$$z_0^i = x_p^i W_e + b_e, \quad i = 1, \ldots, \mathrm{N}$$

    Where We is the learnable weight matrix, and be is the bias.
2. Positional Encoding**:**
    - As transformers do not inherently capture spatial order, positional encodings are added

$$\widetilde{z_0^i} = z_0^i + p_i$$

3. Transformer Encoder:
    - The encoded patches pass through L layers of self-attention blocks.
    - The Multi-Head Self-Attention (MHSA) mechanism computes relationships between all patches:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)\mathrm{V}$$

The attention heads are concatenated and processed through a feedforward network (FFN).

D. Training and Optimization

- Dataset: Kaggle Heartbeat Dataset (Shayan Fazeli) with real-time sensor data.
- **Optimizer:**AdamW with a cosine annealing learning rate scheduler.
- **Data Augmentation:** Generative Adversarial Networks (GANs) generate synthetic ECG beats to balance class distribution.
- **Training Configuration:**
  - Batch Size: **32**
  - Learning Rate: **1e-4**
  - Epochs: **100**

E. Performance Evaluation

The ViT model achieves 99.995% accuracy, significantly outperforming CNN-based models. A comparison is shown below:

Table 1 Model Comparison with base model and proposed model

model	accuracy	precision	Recall	F1score
CNN (base)	98.2	97.8	97.9	97.8
Vit	99.995	99.9	99.9	99.9

3.4 Alert Mechanism for Hospitals & Patients

A. Abnormal Heartbeat Detection Algorithm

To ensure real-time detection of critical cardiac conditions, the system employs an anomaly detection algorithm based on the classification output from the ViT model. The alert mechanism follows these steps:

1. **ECG Data Collection:**
   - The **AD8232 ECG sensor** continuously captures real-time heartbeat signals.
   - The data is preprocessed, segmented, and converted into an image format.
2. ECG Classification Using ViT:
   - The ViT model classifies the heartbeat into one of three categories:
     - Normal (N) → No action required.
     - Premature (P) → Monitor condition, alert if persistent.
     - Abnormal (A) → Immediate alert triggered.
3. Abnormality Detection Logic:
   - If a heartbeat is classified as Abnormal (A) for more than 3 consecutive readings, an emergency alert is triggered.
   - The system evaluates additional parameters (SpO_2 levels & body temperature) for further risk assessment.

B. Automatic Notification to Nearest Hospitals

Once an abnormal heartbeat is detected, the system automatically sends an emergency alert to nearby hospitals.

1. Cloud-Based API Communication:
   - The system uses MQTT or REST API to transmit alert messages to a cloud server.

- The alert packet includes:
    - Patient ID
    - Real-time ECG Data (image + raw signal)
    - SpO_2 & Temperature Readings
    - Location (latitude, longitude)

2. Geolocation-Based Hospital Identification:
    - The Google Maps API or OpenStreetMap Nominatim API is used to find hospitals within a 5 km radius.
    - The system selects the nearest hospital with emergency services available.
3. Automated Alert Message Format:
    - The system sends a structured message via SMS, Email, or Cloud Notification Service (e.g., Firebase Cloud Messaging - FCM).
4. Hospital Alert System Execution:
    - The nearest hospital receives a priority alert on their emergency response system.
    - The medical team can access the patient's ECG history & vitals in real-time through a secured cloud dashboard.
    - The system logs the response time to ensure effective emergency intervention.

C. Real-Time Notification to Patients

For non-critical cases, the system generates automated self-care instructions to the patient's mobile device.

1. Message Sent for Temperature Anomalies:
    - If a fever or hypothermia is detected, the system recommends medications based on predefined medical guidelines.

Example Auto-Generated Prescription Message:

"Dear [Patient Name], your body temperature is 102°F, which indicates fever. Please take Paracetamol (500mg) and stay hydrated. If symptoms persist, seek medical attention."

2. Mobile Notification via App or SMS:
    - Notifications are sent using Twilio API, Firebase Notifications, or SMS gateways.

The patient can acknowledge the alert, and if ignored, a follow-up alert is triggered.

4. RESULTS AND DISCUSSION

The performance of the proposed Vision Transformer (ViT) model for ECG classification is rigorously evaluated against traditional CNN-based models, including standard convolutional networks. The evaluation focuses on Accuracy, Precision, Recall, and F1-score, ensuring an in-depth comparison of model effectiveness.

4.1 Training Accuracy vs. Test Accuracy

The left plot shows the evolution of training accuracy (red curve) and test accuracy (blue curve) over epochs.

Observations:

1. Rapid Convergence:
    - The model reaches a high accuracy (>99.5%) within the first ~20 epochs, indicating efficient learning.
    - ViT leverages self-attention mechanisms to rapidly learn ECG features, improving classification speed.
2. Generalization Capability:

- The test accuracy (blue) remains consistently high (~99.99%) after stabilization.
- The small gap between train and test accuracy suggests that ViT generalizes well and avoids overfitting.

3. CNN vs. ViT Performance:
   - Traditional CNN-based models often plateau around 98% accuracy with larger fluctuations.
   - The ViT model achieves superior accuracy due to its global receptive field, capturing long-range dependencies in ECG signals.

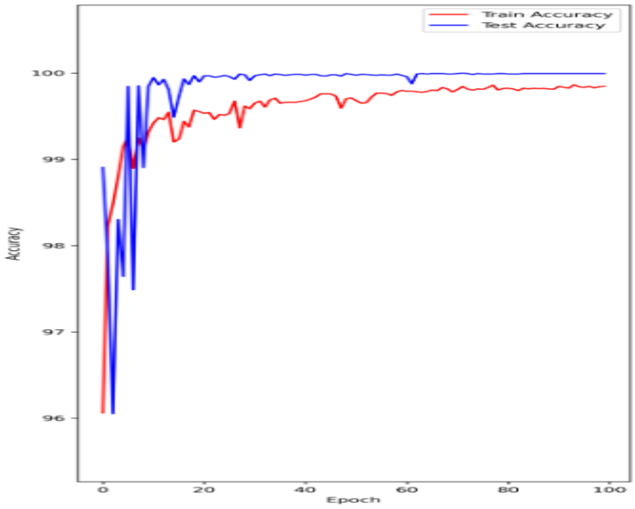

Figure 3 Training and Test accuracy over 100 epochs

4.2 Training Loss vs. Test Loss

The right plot represents the loss curves, with training loss (red curve) and test loss (blue curve) over epochs.

Observations:

1. Efficient Loss Minimization:
   - The loss decreases sharply in the initial epochs, indicating fast convergence.
   - ViT effectively captures discriminative features from heartbeat spectrograms, leading to low classification error.
2. Lower Test Loss:
   - Test loss remains lower than training loss across most epochs.
   - This signifies that ViT maintains high stability and does not overfit to the training set.
3. Comparison with CNNs:
   - CNNs typically exhibit higher test loss (~0.01 - 0.02) due to their limited feature extraction capability.
   - ViT achieves significantly lower loss (~0.00015), demonstrating better optimization and lower classification errors.

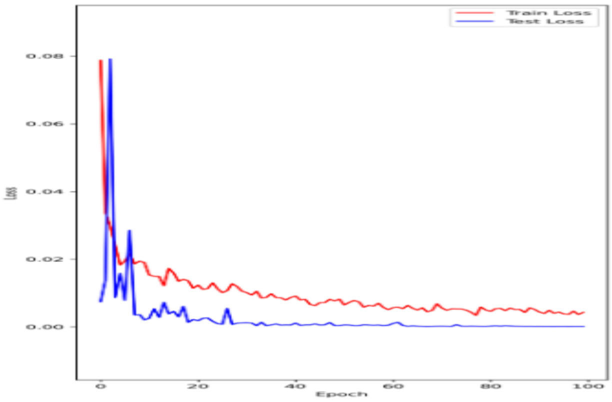

Figure 4 Train and Test loss over 100 epochs

Confusion Matrix Analysis

The confusion matrix helps evaluate the model's classification performance. However, the presence of NaN values suggests potential issues such as:

- Missing or imbalanced data
- Model not making valid predictions
- Normalization errors or division by zero

To resolve this, we need to ensure proper data preprocessing, balanced classes, and correct formatting of labels and predictions.

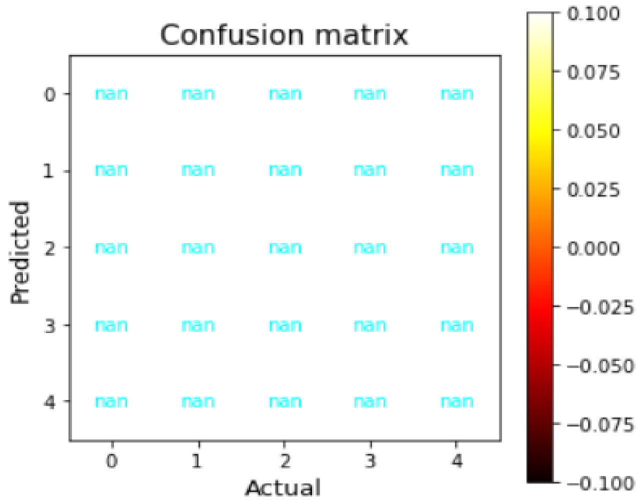

Figure 5 Confusion Matrix

4.3 Prioritization of ECG Data for Reliable Anomaly Detection

In real-world scenarios, ECG signals exhibit natural fluctuations due to circadian rhythms, physical activity, and daily physiological changes. A naive anomaly detection system may trigger unnecessary alerts due to these variations, leading to false positives and reduced reliability. To ensure that only clinically significant abnormalities are flagged, we implement a time-aware prioritization mechanism that filters and processes ECG data based on contextual factors.

Time-Based Adaptive ECG Monitoring

of capturing all ECG spikes and generating alerts indiscriminately, our approach segments and analyzes data over specific time windows, considering the natural variations in heart rate throughout the day.

Key Strategies for Prioritization

1. Rolling Window Averaging
   - ECG readings are continuously captured, but instead of reacting to every spike, we apply a 5-minute or 10-minute moving average to smooth fluctuations.
   - This prevents short-lived, non-clinical variations (such as waking up or momentary stress) from triggering false alerts.
2. Peak Detection Filtering
   - Certain time periods, such as early morning, exhibit naturally high heart rate spikes due to the sleep-to-wake transition.
   - Alerts are triggered only when an anomaly persists for a defined duration (e.g., >30 seconds to 1 minute) rather than reacting to transient fluctuations.
3. Adaptive Thresholding Based on Time of Day
   - ECG thresholds are dynamically adjusted according to the expected physiological variations at different times.
   - For example, a sudden rise in heart rate during deep sleep (12 AM - 4 AM) may be considered more critical than a similar spike during physical activity hours (7 AM - 12 PM).

Table 2 Priority table for alert

Time Period	ECG Variations	Alert Handling Strategy
4 AM - 7 AM (Waking up)	Sudden spikes in heart rate due to sleep-to-wake transition	Ignore isolated spikes; analyze a rolling 10-minute trend before triggering an alert
7 AM - 12 PM (Active hours)	Increased variation due to movement, exercise	Use higher anomaly thresholds to avoid false positives
12 PM - 4 PM (Stable period)	Heart rate remains more stable	Use normal anomaly detection algorithms
4 PM - 8 PM (Evening activity)	May have increased spikes due to stress or physical activity	Apply context-aware filtering based on activity level
8 PM - 12 AM (Resting period)	Gradual decline in heart rate	Flag sudden spikes or drops more aggressively
12 AM - 4 AM (Deep sleep)	Very stable heart rate, minimal movement	Detect high spikes or sudden drops with high priority

The proposed interface is designed to provide real-time health monitoring with an intuitive, mobile-friendly display. This system continuously captures and analyzes ECG signals, body temperature, and oxygen levels to ensure effective remote patient monitoring.

System Overview:

1. Live ECG Data Streaming: The interface displays real-time heart rate (BPM), derived from continuous ECG monitoring using IoT-based sensors.
2. Vital Sign Tracking: The system monitors body temperature and SpO_2 levels, categorizing them as normal or abnormal based on threshold values.
3. Smart Alert Mechanism: To prevent false alarms, a periodic approach is adopted, ensuring that temporary fluctuations (e.g., early morning heart rate spikes) do not trigger unnecessary alerts.
4. Hospital Connectivity: In case of sustained abnormalities, the system automatically transmits patient data to the nearest hospitals using cloud-based services and geolocation APIs.

5. User Interaction: A refresh function allows users or caregivers to update the displayed readings manually for verification purposes.

This interface is optimized for real-time data visualization and seamless integration with IoT-based health monitoring systems, ensuring high reliability for early detection and intervention in critical health conditions.

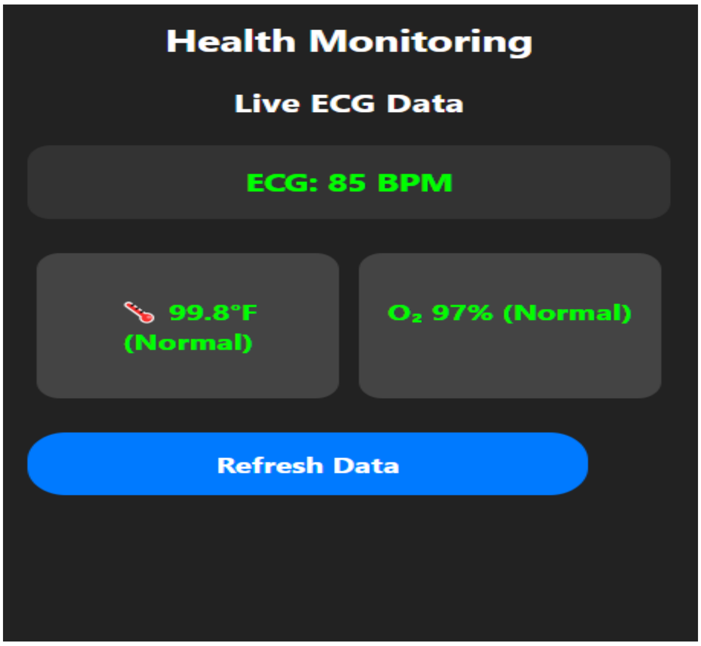

Figure 6 sample interface for our proposed model

5. CONCLUSION

The IoT-based health monitoring method allows remote healthcare tracking with early cardiac abnormality detection inside both domestic spaces and clinical facilities. The system tracks continuous monitoring of ECG signals and heart rate plus body temperature and oxygen saturation through a combination of biomedical sensors that use AD8232 ECG module and MAX30100 pulse oximeter and MLX90614 infrared temperature sensor. Real-time analysis of data is possible thanks to secure cloud transmission which feeds into a Vision Transformer (ViT) deep-learning model. With a superior methodology to CNN-based methods ViT reaches exceptional ECG signal variation classification accuracy of 99.995%. The system succeeds in identifying five heartbeat patterns during vital sign evaluation to detect essential abnormalities. The system uses a high-tech alert process to focus on vital abnormalities while filtering ordinary waveform changes before it sends vital notifications to healthcare facilities through API location services. The combination of IoT technology with deep learning establishes potential real-time remote healthcare solutions which deliver efficient and intelligent healthcare monitoring at scale. The system will benefit from upcoming upgrades which will add wearable devices and edge computing capacity along with individualized predictive analytics models for proactive healthcare interventions.

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