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International Journal of Innovations in Science & Technology

Heart Sense: A novel IoT integrated Deep Learning Based ECG Image Analysis for Enhanced Heart Disease Prediction

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Citation | Ghilzai. R. J, Bibi. U, Umer. H. G. A, Rubab. S, "Heart Sense: A novel IoT integrated Deep Learning Based ECG Image Analysis for Enhanced Heart Disease Prediction", IJIST, Vol. 7 Issue. 1 pp 336-357, Feb 2025

Received | Jan 26, 2025 **Revised |** Feb 16, 2025 **Accepted |** Feb 18, 2025 **Published |** Feb 19, 2025.

The IoT based advancements in the healthcare networks leveraging the unmatched capabilities of the Internet of Things for various fatal disease prediction and remote health monitoring that proved to be very beneficial in providing timely and accurate healthcare services to patients. Patients who are suffering from chronic diseases like blood pressure, kidney diseases, and heart diseases need treatment on time to avoid sudden deaths due to these ailments. To avoid this serious scenario, we have presented a novel approach for predicting heart diseases based on the Internet of Things. By leveraging the combined abilities of The IoT and Deep learning we have proposed an advanced approach that will able to predict heart diseases with increased accuracy and precision in comparison to the existing approaches along with providing timely notifications to both patients and the medical professionals to deal with the situation at hand most effectively.

We will be receiving real-time health data from the sensors which will be a wearable IoT device in our case. This collected data contains the continuously monitored information of the patient's ECG using an ECG sensing system that is sent to the cloud for precise disease prediction. We will also be employing the patients 'electronic health records which will contain ECG images to increase the accuracy of our results. The Deep Learning model called the transformer will be used in the proposed approach for the precise prediction of cardiovascular disease in real-time. Both the healthcare professionals and the patients are provided with the relevant information if an ailment is predicted for effective healthcare monitoring and treatment. The proposed model has better results than the existing approaches for the prediction of heart disease in terms of accuracy which is 99.8%.

Keywords: Cardiovascular disease prediction, IoT, sensors, Deep learning, Transformer, ECG Images, Heart disease prediction

Introduction:

Rate of sudden cardiac death among people varies from 40 to 100 out of an approximate total of 100,000 individuals [1] Convolutional neural networks (CNNs) are widely used for image classification tasks and disease prediction based on electrocardiograms. CNNs employ convolutional filters, which work best with confined patterns in space, to extract features at several layers. Due to their inability to detect global contextual information and long-range dependencies, medical image analysis objectives surpass CNN's capabilities. On the other hand, a Vision Transformer (ViT) maintains prolonged connections between parts in ECG images by utilizing self-attention capabilities. By converting images into patch sequences, the ViT system employs a different technique than CNNs because it provides superior global representation learning over fixed receptive fields. ViT's basic architectural approach enables us to achieve great success following data augmentation for any dataset while keeping a significantly lower baseline, outperforming CNN models in terms of accuracy. ViT's improved performance in our study demonstrates its capacity to identify hitherto unknown changes in ECG data, making it a great option for assessing heart illness using Internet of Things platforms.

Cardiovascular diseases or ailments related to the heart are considered as one of the most lethal diseases that not only affect the heart's functionality but also, introduce critical issues like a decrease in the blood vessel function and the infection of the coronary artery. These complications result in a sudden heart attack and stroke [2].

The major symptoms that show the existence of cardiovascular disease in people according to a survey are pressure, shortness of breath, tightness of the chest, pain in the chest, pain in the abdomen, neck pain, leg chills, fatigue, loss of weight, bradycardia, syncope, swelling of legs, tachycardia, dizziness, changes in skin color and light headiness. With the occurrence of different heart or cardiovascular diseases like heart failure, congenital heart disease, dilated cardiomyopathy, myocardia, arrhythmia, and mitral regurgitation, these symptoms vary [3].

Heart disease is a condition that impacts both men and women, but males are at greater risk of developing it. One in four deaths in 2009 were related to heart disease. 525,000 of the 735,000 US citizens who suffer from heart attacks encounter it for the first time. It is a second attack on the remaining 210,000 people [4]. People with SCD can pass away in a matter of minutes and when SCD strikes without the presence of an automated external defibrillator (AED) or paramedics, a life that could have been spared is lost [5].

Age, heredity, drug misuse, smoking, sexual behavior, elevated blood pressure, cholesterol, physical inactivity, obesity, diabetes, stress, and poor hygiene are among the risk factors for heart disease [6]. As heart disease is so dangerous, diagnosing it requires screening. Doctors perform blood pressure, blood glucose level, cholesterol, electrocardiography (ECG), ultrasound, cardiac computer tomography (CT), calcium scoring, and stress testing as part of the screening process [7]. This screening method necessitates human interaction and a variety of strenuous physical engagements [8]. This demands a need for an automated system for complicated and complex heart diseases so that efficient, effective, and correctly timed results can be obtained. IoT and Artificial intelligence AI have demonstrated a huge part in this scenario for the acquisition of an accurate predictive system.

The significant developments in ICT over the past few decades, especially the IoT (Internet of Things), have created a plethora of opportunities in the eHealth space [9][10][11]. These developments have allowed electronic health systems to progress and get better despite challenges with data management, privacy protection, and information security [12][13][14]. The application of the various Internet of Things (IoT) based wearable sensors to evaluate human behavior and ascertain health status has grown in importance in the modern day. The medical industry makes extensive use of these wearable sensors, and (IoT) Internet of Things technology facilitates data collecting by providing decision-making tools [15][16]. Because it is difficult for humans to extract critical medical information from the massive amount of data that is maintained and shared by several health research institutions globally, cloud computing platforms are often used for illness diagnosis. As a result, the majority of people find that the current medical system demands a significant investment of time and energy to produce the correct medical diagnosis. The creation of wearable medical equipment that can provide extremely accurate medical diagnostics is desperately needed to address this issue [17][18][19][20].

The various computational models and the development of applications that are based on IoT offer enormous benefits for tracking cardiovascular risks [21]. Physicians no longer need to use intrusive devices like cables or straps to readily track and record vital signs and other medical data. Moreover, doctors can make well-informed recommendations regarding therapies or devices that could assist prevent or help in treating the illness due to the precision through which these systems gather data on the patients. Due to the ease and low cost of patient diagnosis, this results in time and financial savings. Doctors may more rapidly and effectively access patient medical histories and data thanks to the increasing digitization of health records, enabling them to make more knowledgeable decisions regarding medicine and preventive care. This makes it possible to effectively manage the patient's condition over the long run and reduces the chance of subsequent medical issues [21][22].

Remote cardiac patient monitoring is now possible thanks to the proliferation of sensor-equipped wearables and smart, networked gadgets facilitated by the pervasive Internet of Things. IoT devices employed for monitoring the health of patients include blood pressure monitors, wearable electrocardiogram (ECG) monitors, and smart health watches. Critical patient data or information can be securely stored in the cloud with the aid of the Internet of medical devices. Then, using past electronic clinical information and sophisticated deep learning algorithms, cardiac risk can be reliably diagnosed. Devices connected to the Internet of Things can quickly inform caregivers and medical experts about a patient's condition. This helps physicians to make timely decisions for patients as well as the population at large by evaluating the probability that a patient will have a particular cardiovascular or heart disease, their diagnosis for a particular condition, and the appropriate course of therapy [23].

The diagnosis and treatment of ailments have been changed by advances in AI (artificial intelligence), operative instruments, and mixed-reality applications, which have outperformed earlier levels of effectiveness. As a result of this advancement, clinical DSS (decision support systems) that are particularly good at identifying electroencephalogram (EEG) and electromyography (EMG) data have been developed. When it comes to diagnosis, AI-based techniques have proven to be more accurate than manual ones. In addition, the precision of machine learning (ML) models has excelled that of human medical practitioners and imaging professionals. It is now feasible to precisely ascertain a patient's present state of health and the grievousness of their ailment through intelligent diagnostics, allowing customized treatment regimens to be established [24][25].

Artificial intelligence aids in the analysis, detection, and diagnosis of illnesses. In addition, AI techniques correctly classify illnesses. As a result, numerous AI algorithms are developed to promptly and reliably forecast diseases at an earlier stage [26]. The development of Machine Learning (ML) techniques has enhanced the healthcare industry by streamlining the process of identifying diseases. It is especially advantageous for those who live in remote and rural places. Heartbeats and blood pressure readings are used to track and monitor physical wellness. Reliable disease diagnosis is often achieved with the use of machine learning ML and deep learning DL technologies. They can categorize illnesses and forecast anomalies [27]. Deep learning models solve problems such as the inadequacy of ML algorithms' huge data analysis capabilities. Deep learning techniques contain more hidden layers and are taught on the original, vast amount of data, increasing prediction accuracy. To improve prediction accuracy, more structured and unstructured data methods have been introduced [12].

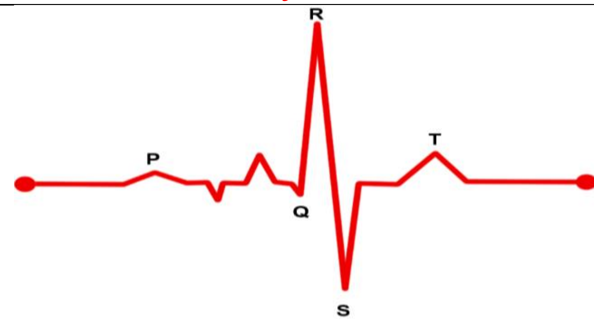

Figure 1. A normal ECG Signal.

The ability to perceive the electrical symphony of the heart through the electrocardiogram (ECG) is a priceless artistic talent. Its easy attention to detail grants a domain of knowledge. The ECG can provide important insights into the advancement of an MI myocardial infarction, the existence of numerous cardiac arrhythmias, and the impact of high blood pressure [25][28]. The complexity of disease detection and the advancement of imaging techniques have led to an increase in the quantity of medical images. Segmentation is used to remove the biological area of attentiveness from a medical image's background. During the segmentation process, the image will be divided into many sections according to their significance to diseases, organs, and other biological entities. During the image processing segmentation process, low contrast values and the frequency of raw values that produce noise are taken into account. An important aspect of image analysis is the automatic segmentation procedure [29].

The precision of segmentation dictates whether a disease diagnosis system succeeds or fails. The accuracy of the segmentation process has increased with the use of manual techniques or methods and contemporary mathematical approaches, such as illumination, PCA (principal component analysis), convex property, partial differential equation, thresholding, and the important material characteristics or features of the images. Sturdy segmentation methods make illness assessment easier [30].

The paper is formulated in the way that in section 1 introduction of the study is presented and in section 2 literature review explaining different IoT-based heart disease prediction systems is described. Then comes the proposed methodology in section 3 after that experimental setup for evaluating the model is presented in section 4 and then the outcome or results of these conducted experiments are shown in section 5. In the last, in section 6 conclusion of the study is stated.

Table 1: A literature review of methods used by various researchers for HDP using IOT.

Published Year	Author Name	Methods used	Dataset	Features considered	Accuracy / Results
2024 [31]	Alzakari et al.,	XGBoost for feature selection Bi-LSTM for finding sequential patterns from data.	Combination of regular medical monitoring data and ECD (Electronic Clinical Data).	Blood pressure, heart rate, oxygen saturation, respiratory rate	99.4%
2024 [32]	Rajaganapathi et al.,	ML algorithms (CNN) for data analysis to detect symptoms of	2 datasets from the UCI repository an arrhythmia	Heart rate, blood pressure, pulse	94.72%

		cardiovascular disease. The system alerts users when their readings are abnormal, aiding them in taking precautions.	dataset and a Cleveland dataset i.e. a heart disease dataset. PASCAL data set.	oximetry, sleep patterns	
2024 [23]	Liao et al.,	A multilayer perceptron artificial neural network that integrated a genetic algorithm and an error-back propagation approach.	794 patients, 524 individuals with heart attacks, and 571 individuals with congestive heart failure.	Age, sex, cholesterol, peak heart rate, heart attack due to physical exertion	97.82%
2019 [33]	Al-Makhadmeh & Tolba	Wearable watch for collecting different data. Higher order Boltzmann network approach inspects the connectivity of features in the search space. After the feature training, the deep belief network function is deployed to the network for classification.	UCI machine learning repository dataset.	Heart rate, blood pressure, blood glucose level	99.03 %
2023 [34]	Malibari	LWADCNet to forecast the patient's disease. The global depth-wise convolution (GDWConv) feature reconstruction technique and Depthwise separable convolution (DSC) residual architecture serve as the foundation for the EO-LWAMCNet. SoftMax function	CKD and HD datasets.	Blood pressure, hypertension, history of diabetes, serum, albumin	94% (HD) 93.5% (CKD)

		used in fully connected layer for classification.			
2024 [35]	Satpathy et al.,	A fuzzy inference system (FIS), is used for the categorization of heart disease risk. (A fuzzifier, an inference engine, a knowledge base, and a defuzzifier). FPGA applied for swift risk prediction.	Cleveland dataset from the UCI repository.	Age, sex, cholesterol, resting BP, Maximum heart rate, fasting blood sugar	98.8%
2024 [36]	Tang et al.,	An SH-CSO technique, and classification using an evolving fuzzy neural network based on Shamble Shepherd.	UCI dataset of diseases like diabetes, kidney difficulties, and heart disease.	Gender, age, blood sugar level, heart rate, breathing rate	97.26 % for diabetes and 96.16 % for heart disease.
2024 [37]	Rehman et al.,	The system includes a real-time monitoring framework. AI algorithms predict Sudden Cardiac Death (SCD) risk. Emergency alerts are sent to community healthcare workers.	The ECG signal data from a wearable device.	ECG signal data	Power consumption 33 mA distance 27 m

Objectives:

The main objectives of our study are:

- **Early Detection of Heart Diseases** – To introduce an advanced IoT-integrated deep learning approach for the early and precise prediction of heart diseases.
- **Real-Time Health Monitoring** – Utilizing wearable IoT devices to continuously monitor ECG data and transfer it to the cloud for real-time disease prediction.
- **Improved Diagnosis Accuracy** – Deploy a Vision Transformer (ViT) model to increase the precision and accuracy of heart disease classification using ECG images, surpassing existing models like CNN, VGG16, and ResNet50.
- **Timely Alerts and Notifications** – Deliver instant notifications to both patients and healthcare professionals after detecting potential heart conditions for immediate medical intervention.
- **Integration of IoT and Deep Learning** – Leverage the combined power of IoT and deep learning DL to automate the diagnosis process and decrease the requirement for manual interpretation of ECG data.

- **Enhanced Predictive Model Generalization** – Ensuring the model remains effective even with diverse datasets by including techniques like data augmentation and transfer learning.
- **Efficient Remote Patient Monitoring** – Reducing the dependency on in-person hospital visits by allowing remote monitoring of patients' cardiac health through cloud-based systems.
- **Comparison with Existing Models** – Evaluating the performance of the proposed study against traditional machine learning and deep learning models to showcase its superiority.
- **Future Scope for Privacy and Security** – Highlighting the requirement for robust security mechanisms to protect sensitive patient data in future implementations.

Novelty Statement: By leveraging the combined abilities of The IoT and Deep learning we have proposed an advanced approach that will able to predict heart diseases with increased accuracy and precision in comparison to the existing approaches along with providing timely notifications to both patients and the medical professionals to deal with the situation at hand most effectively.

Literature Review:

To extract exact information and accurately infer the conclusion, a novel data fusion strategy based on type-2 fuzzy logic (T2FL) combined with Dempster-Shafer theory (DST) is proposed [38]. The type-2 fuzzy logic in the suggested scheme effectively determines the membership values of the patient data, and the DST in the decision-making system appropriately fuses and processes the evidence derived from the membership values. The presented method executes significantly better considering decision accuracy than the current schemes based on ontology and type-1 fuzzy logic, according to an extensive computer simulation using a dataset of diabetes and heart disease.

In [37] proposed a study that suggests using real-time ECG signal monitoring and uploading the data to the cloud to predict Sudden Cardiac Death (SCD). In contrast to earlier research, the suggested approach includes a second emergency response mechanism that notifies local community healthcare providers when SCD is expected to happen.

In [33] proposed a medical device that deploys the (IoT) Internet of Things to gather patient cardiac data both before and after heart illness. The higher-order Boltzmann deep belief neural network is employed to process the data, which is sent continuously to the medical center or infirmary (HOBDBNN). The deep learning approach utilizes complex data effectively to obtain efficiency by learning aspects of heart disease from past examinations. After performing experiments, the system's significance is evaluated by considering metrics such as the receiver operating characteristic (ROC) curve, f-measure, sensitivity, specificity, and loss function. By reducing the difficulty of detecting heart illness, the HOBDBNN approach and IoT-based analysis significantly minimize heart disease mortality with 99.03% accuracy and minimum time complexity (8.5 s).

In [23] proposed a study, in which a multilayer perceptron artificial neural network ANN with a genetic algorithm and an error-back propagation approach was used to evaluate two cardiac diseases. Given the growing amount of patient data and the widespread usage of ECR (electronic clinical records), artificial neural networks' capacity to process continuous time series data is essential for resource optimization in smart electronic health systems. More precise prediction models must be developed to achieve this. The suggested system uses Internet of Things (IoT) sensors to collect data, which is then employed for conducting predictive analytics on ECD electronic clinical data relating to patient history that is stored in the cloud. A smart healthcare system with a coverage error of 97-94%, accuracy of 97-89%, sensitivity of 97-96%, and specificity of 97-9.99% can precisely observe and predict the probability of heart ailment through the application of Mu-LTM (multidirectional long-term memory). With an F1-score of 97.55% and precision of 96.71%, our smart heart disease prediction system performs quite well when compared to others.

An Internet of Things (IoT)-based system that could aid in the development of a Consumer Electronics (CE) product has been presented by [35]. Based on Internet of Things technology, this system will notify the user whenever any parameter related to the heart shifts from the expected limit. Through a mobile application, the data gathered by this system is delivered to an analysis system built around a Field Programmable Gate Array (FPGA), after which it is moved to the cloud for storage. A wearable IoT device can be used to display this raw data, and the system will manipulate the data appropriately. The creation of a fuzzy classifier that can precisely forecast the chronic state of a disease is the main innovation of this proposed research. When compared to other methods, the execution time of a fuzzy classifier implemented with FPGA is significantly shorter, at 57.7 microseconds. Additionally, the suggested model's accuracy of 98.8% is higher than that of other machine learning models, which are 97%, 96.5 %, and 93.2% for SVM, KNN, and Decision Tree models, respectively. Earlier models, including NB (Naive Bayes), DT, SVM, and KNN.

In [34] the EO-LWAMCNet model, an EO optimized Lightweight Automatic modulation classification network, to accurately predict a patient's pathological health condition (heart or kidney disease). Every piece of data that is gathered by an implanted sensor in the body of the patient is transmitted to the cloud through a gateway. The EO-LWAMCNet model starts the classification procedure to predict chronic disease based on the data obtained from the sensor. There is a training and testing phase for the model. HD and CKD databases are used to forecast the illness. Here, the training stage uses the preprocessed data for classification. The Cloud server's (CS) sensor data is examined and classified into abnormal (heart or renal disease) and normal when the training procedure is finished. In the scenario of an abnormal outcome, the doctor requires an awareness message to treat the patient. Model performance is assessed using the following metrics: accuracy, miss rate, MCC, and F1-score. With a 93.5% accuracy rate when applied to the CKD dataset and a 94% accuracy rate when applied to the HD dataset, this model can reliably forecast the existence or absence of heart or kidney disease. Additionally, the model's miss rate for categorization is lower.

To efficiently monitor cardiovascular risks, the research presented by [32] investigates computational models and application development made possible by the Internet of Things (IoT). The main reason behind the death worldwide is cardiovascular illnesses, and at the moment, there are insufficient extensive and trustworthy monitoring systems to determine the chance of developing these conditions. With the use of IoT, it is possible to combine data from several sources, including nutrition, physical activity, BMI, and environmental factors, to create a comprehensive tracking tool that is capable of accurately estimating cardiovascular risk. Personalized health coaching can be provided by the developed application, which uses machine learning algorithms to spot trends and modify a user's healthcare path. In the end, this research evaluates how well IoT technology can monitor automotive cardiovascular risks and be integrated into existing healthcare systems.

By merging physical data from patients' normal medical monitoring with Electronic Clinical Data (ECD) from comprehensive medical records, [31] proposed a methodology that delivers higher accuracy. This novel method advances the field of heart illness prognosis. A method that addresses this need by utilizing state-of-the-art IoT technologies and machine learning algorithms. Specifically, we employ the potent Extreme Gradient Boosting (XGBoost) technique to effectively process large datasets and derive significant features to enhance prediction precision. Bidirectional Long Short-Term Memory (Bi-LSTM), a deep learning model, is utilized to improve prediction abilities and extract intricate temporal patterns from patient data. It achieved a higher prediction accuracy of 99.4% using our approach, outperforming naive Bayes NB, decision trees DT, and random forests RF. This work presents a novel method for remote healthcare monitoring using a combination of advanced machine learning models and Internet of Things technologies.

The goal of the research developed by [36] is to create a model that combines AI and IoT techniques to diagnose diabetes and cardiovascular illnesses. Data collection, preprocessing, classification, and parameter setup are all incorporated in the suggested model. The Internet of Things' wearables and sensors make it simple to collect data, and artificial intelligence techniques exploit that data to identify diseases. The suggested method uses the Smart Healthcare-Crow Search Optimization (SH-CSO) algorithm to detect ailments as an illustration of intelligent healthcare systems. CSO improves medical data classification by modifying the "weight" and "bias" parameters of the intelligent healthcare systems model. The intelligent healthcare systems model's diagnostic results are considerably enhanced by the use of CSO. The intelligent healthcare systems model's diagnostic results are considerably enhanced by the use of CSO. Using medical records, the SH-CSO algorithm's effectiveness was confirmed. The proposed SH-CSO model was able to detect diabetes with a greatest accuracy of 97.26% and heart disease with a maximum accuracy of 96.16%, according to the results.

To integrate ensemble deep learning in Edge computing devices, [39] presented a unique framework called HealthFog and implemented it for an autonomous analysis of heart disease in the actual world. Using Internet of Things (IoT) devices, HealthFog provides healthcare as a fog service and effectively maintains heart patient data in response to user queries. The suggested model's significance is employed and evaluated using the fog-enabled cloud framework FogBus, to power consumption, network bandwidth, latency, jitter, accuracy, and execution time. HealthFog can be designed to work in some ways to meet the needs of different users and in a variety of fog computation scenarios, all while delivering the best quality of service or predictive accuracy. Table 1 shows a detailed overview of the literature on Heart disease prediction.

Numerous research mentioned in the literature above has examined various machine learning and deep learning approaches, such as CNN, XGBoost, Bi-LSTM, and fuzzy inference systems, in the context of IoT-based heart disease prediction. Despite their difficulties with speedy data processing, both approaches showed good precision rates through runtimes on predetermined medical data and manual feature-gathering techniques. Our method creates a Vision Transformer (ViT) model to process ECG images directly without the need for human feature engineering. Because it can identify spatial patterns in ECG images, a transformer-based design improves the predictive model's performance over state-of-the-art methods, achieving 99.8% accuracy.

Although IoT has proved its worth in efficiently performing well in various healthcare applications it still has some crucial issues. The few concerning complications include the security and the privacy of sensitive patient data, for this robust security and data encryption mechanisms need to be employed which is a quite complicated job. Another important issue to highlight here is the interoperability between the various IoT devices and the communication between them as these devices operate on different communication protocols and a harmony between these protocols is necessary for the effective communication between the devices to perform their respective tasks efficiently. Moreover, another point to be considered is the stability of the connection among the devices and the long battery life needed for these devices to operate perfectly. The management of the huge real-time data generated by these IoT devices is also among the various concerns for efficient remote patient-health monitoring. The security-related concerns will be dealt with in the future work that we plan to conduct for our research.

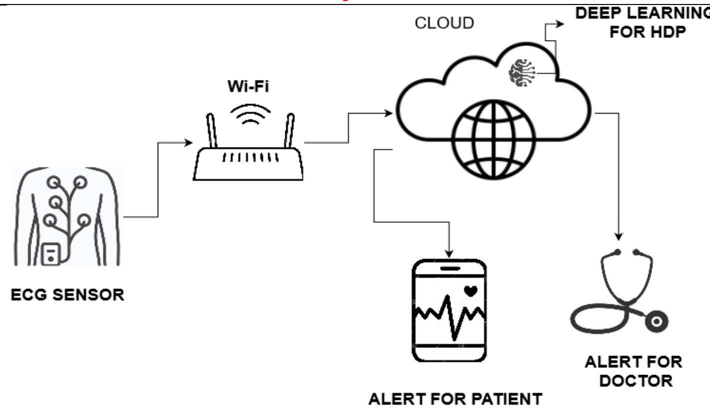

Figure 2. IoT-based HDP Framework.

The Proposed Methodology:

The proposed approach is divided into 2 stages: first real-time data is collected from the IoT sensors, which is an ECG sensing system in our case that is in the form of an easy wearable device that will not disrupt the patients' daily routines it will continuously monitor the patient's ECG data and then this data is transmitted to the cloud where it is manipulated and is checked for the existence of heart diseases using the Deep learning module which will be using the ECG images data to predict the heart diseases. Second, if a heart disease is predicted then an alert will be sent to the doctor and the patient so that this serious issue can be dealt with utmost care and treatment. The proposed IoT-based HDP framework is shown in Figure 2 and its workflow diagram is shown in Figure 6. The overall flow diagram of the various steps conducted in our methodology is shown in Figure 3. Now let's state the detailed steps of how the Deep learning module will work for heart disease prediction.

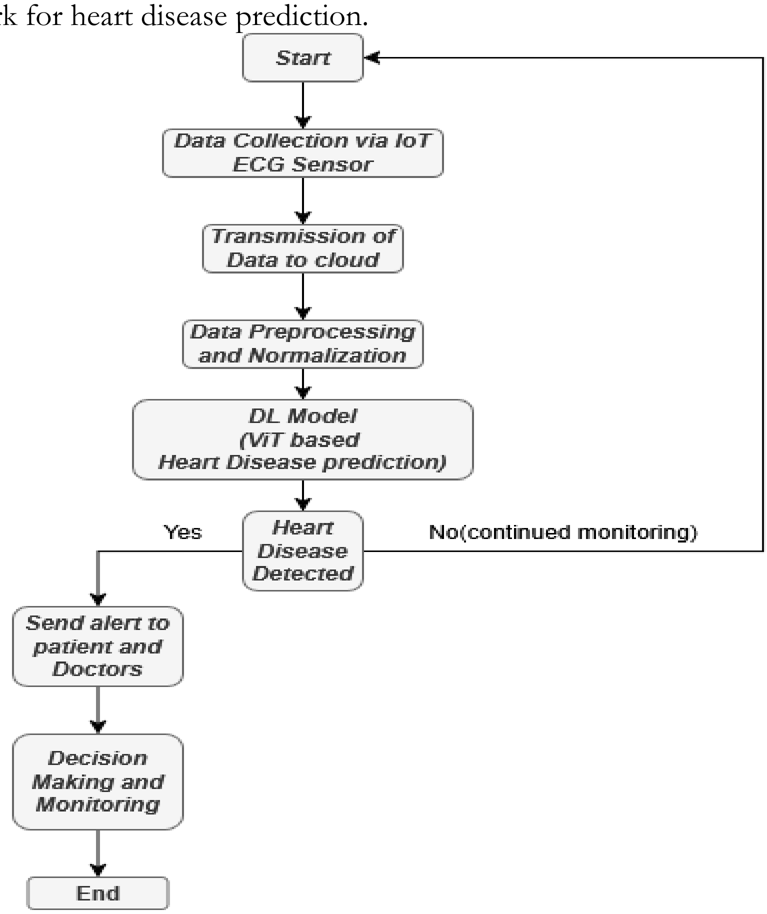

Figure 3. Methodology Flow Diagram

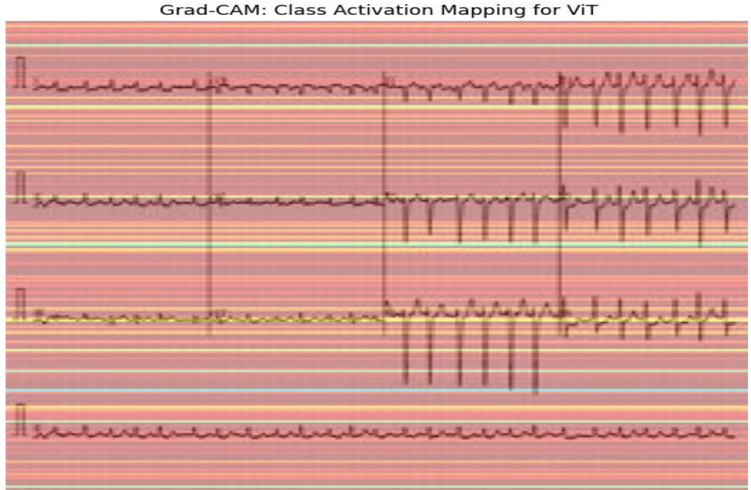

Figure 4. Grad-Cam: class activation mapping for ViT (to show parts of the ECG image model focused on for making predictions).

Data Preprocessing:

First of all the data is needed to be pre-processed to make it free from all kinds of noise and errors for accurate prediction.

Dataset Description:

The ECG images dataset which is being used in our approach is obtained from the Kaggle website. It has a total of 1328 images belonging to 4 classes that are abnormal heartbeat HB, mitochondrial infarction MI, patients with a previous history of MI i.e. PMI, and normal heartbeat i.e. Normal. We have selected 928 images for training and 400 images for testing. The class distribution for the training and the testing set is given in Table 2. The class misbalancing is handled via the SMOTE (synthetic minority oversampling technique) for precise results.

Table 2. Distribution of images for 4 classes in the train and test set.

Dataset	HB	MI	PMI	Normal	Total	Dataset images Source
Training	233	239	284	172	928	Obtained from Kaggle
Testing	100	100	100	100	400	

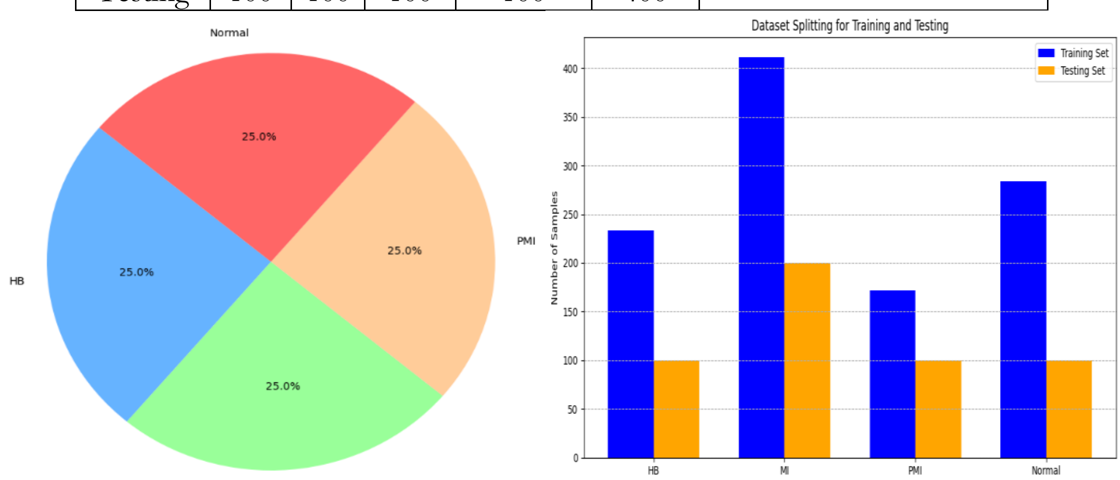

Figure 5. (a) Class distribution in the test set. (b) Class distribution in train and test sets.

Image Resizing and Normalization:

For the basic aim of achieving uniformity in image size and the format of the images required for the accurate model training, all the images are resized to a dimension of 224*224 pixels. After this, the pixel values of the image are normalized to have a mean and standard deviation of 0.5 each. This is done to ensure that the values are centered and exist within the range of -1 and 1. Images are converted to PyTorch tensors as that is the required format for the input to be fed to the Deep Learning Model. These transformations are applied using the torchvision. Transforms library.

Mathematically:

For Resizing Image (224×224): Let the original image be I(a,b) of size M×N (where M is the original height and N is the original width of the image).

Let Scaling factors be:

sa = 224/M, **sb** = 224/N (1)(2)

For representing each pixel in a new image I'(a',b') which is mapped from the original image:

$$I'(a',b') = I\left(\left\lfloor \frac{a'}{s_a} \right\rfloor, \left\lfloor \frac{b'}{s_b} \right\rfloor\right) \quad (3)$$

Where, $I'(a',b')$ Is the resized image of size 224×224 and a' and b' represent pixel positions in the resized image.

Normalizing: Given pixel values p in image I', normalized value p' is:

$$p' = \frac{p-\mu}{\sigma} * \text{ new\_std } + \text{ new\_mean } (4)$$

Where: μ = mean pixel value, σ = standard deviation, new_mean = 0.5, new_std = 0.5

$$p' = \frac{p-\mu}{\sigma} * \ 0.5 \ + \ 0.5 \ (5)$$

Normalization applies to each channel, for RGB images:

$$p'_{\text{channel}} = \frac{p_{\text{channel}} - \mu_{\text{channel}}}{\sigma_{\text{channel}}} * 0.5 + 0.5 \ (6)$$

The tensor conversion scales original pixel values from [0,255] to [0,1] before normalization:

$$p_{\text{tensor}} = \frac{p_{\text{original}}}{255} \ (7)$$

Where: p_{channel} represents the pixel value in a specific color channel (Red, Green, or Blue). μ_{channel} and σ_{channel} are the mean and standard deviation for that channel.

Model Architecture:

We have employed a vision transformer model ViT for this proposed approach and we have used its pre-trained version ViT-base model that has a patch size of 16*16 and an input size of 224*224. This model is then fine-tuned to classify the ECG image input into one of the four classes. The model used the ImageNet dataset for its pre-training and it is fine-tuned on our ECG images dataset.

The output layer has undergone modification to have four output nodes as the number of the corresponding classes in our dataset is four. The model is loaded with the pre-trained weights and the differences that occur in the layer size due to the out shape are handled by the ignore_mismatched_sizes=True argument. Mathematically:

1-Fine-tuning process:

2-Forward Pass:

x → Patch Embedding → Transformer Blocks → Classification Head → Softmax

Loss Calculation:

L = Cross-Entropy Loss (predictions, targets)

3-Backward Pass:

$$\nabla\theta = \partial L/\partial\theta \text{ (computation of gradient) } (8)$$

$$\theta = \theta - \eta\nabla\theta \quad \text{(updating parameter) } (9)$$

Key equations:

Attention Mechanism:

$$\text{Attention } (A, B, C) = \text{softmax}\left(\frac{AB^T}{\sqrt{d_b}}\right) C \ (8)$$

Multi-Head Attention:

$$\text{MultiHead}(A, B, C) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \quad (10)$$

Layer Normalization:

$$\text{LN}(x) = \gamma \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}} + \beta \quad (11)$$

Position Embedding:

$$E_{\text{pos}} \in \mathbb{R}^{(N+1)\times D} \quad (12)$$

Final Classification:

$$p(y \mid x) = \text{softmax}\left(W\text{LN}(z_L^0) + b\right) \quad (13)$$

This implementation maintains the original architecture of the ViT while deploying it for the 4-class ECG classification task through transfer learning.

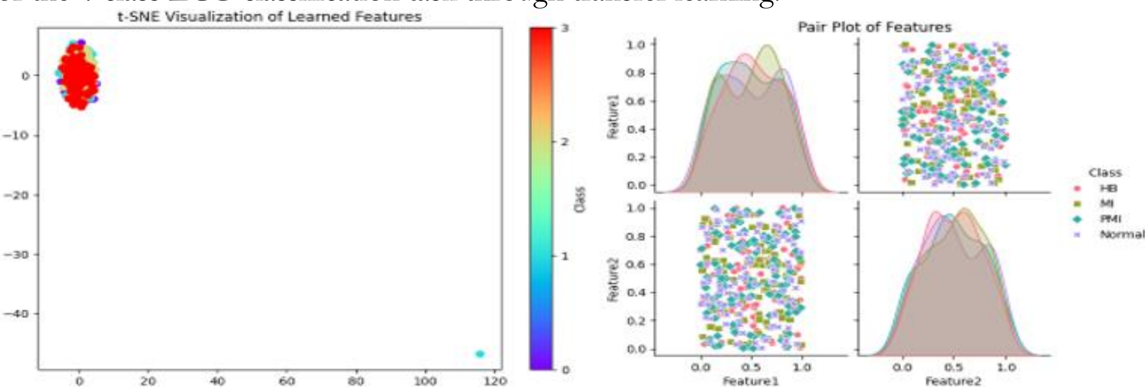

Figure 6. (a) Visualization graph of selected features (t-SNE). (b) Visualization graph of selected features (pair plot).

Model Hyper-Parameters and Training:

The number of epochs used for training the model is 10. The optimizer used for the training process is Adam and the learning rate is 1e-4. The batch size is set to 16. The cross-entropy loss function is used for optimizing the model. During each epoch the model is trained to minimize the loss and the average loss during the epochs is calculated to evaluate the performance of the model. Mathematically, The Training Parameters are: Epochs (E) = 10, Batch size (B) = 16, Learning rate (η) = 1e-4, Total samples (N), Number of batches per epoch = ⌈N/B⌉.

Cross-Entropy Loss Function: For a batch of B samples:

$$\mathcal{L}_{CE} = -\frac{1}{B}\sum_{i=1}^{B} \sum_{c=1}^{4} y_{i,c} \log\left(\hat{y}_{i,c}\right) \quad (14)$$

where:

$y_{i,c}$ is the true label (one-hot encoded)

$\hat{y}_{i,c}$ Is the predicted probability for class c4 is the number of classes Adam Optimizer: For each parameter θ :

First moment estimate:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)g_t \quad (15)$$

Second moment estimate:

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)g_t^2 \quad (16)$$

Bias correction:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^l}$$
$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (17)(18)$$

Parameter update:

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \varepsilon}} \quad (19)$$

Where: $\beta_1 = 0.9$ (decay rate for a first moment), $\beta_2 = 0.999$ (decay rate for a second moment), $\epsilon = 1e\text{-}8$ (numerical stability constant), g_t is the gradient at time t.

Model Testing:

After training the model, it is tested on the test set for accurate heart disease prediction. The model is evaluated using the different evaluation metrics which are:

Evaluation metrics:

The main evaluation metrics on which the proposed model is evaluated are:

The confusion matrix presents a viewable demonstration of the algorithm's performance. The confusion matrix table helps to viewably instigate the prediction errors. The confusion matrix usually consists of four portions: true negatives (TNs), false positives (FPs), false negatives (FNs), and true positives (TPs). The matrix visualizes actual class instances as rows and predicted class instances as columns (or vice versa).

Precision can be stated as the ratio of the true positive TP to the total prediction (TP + FP) made by the model.

$$\text{Precision} = TP / (TP+FP) \quad (20)$$

Accuracy The overall number of accurate predictions out of all the predictions is known as accuracy.

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN) \quad (21)$$

A recall is also called sensitivity or the true positive rate. It is the proportion of positive observations that are correctly predicted with the overall number of positive observations.

$$\text{Recall} = TP / (TP+FN) \quad (22)$$

F1-Score is calculated by taking the average of precision and recall. This metric has generally been recognized to be a valid approach for comparing the performance of various classifiers, specifically when the data is unbalanced.

$$\text{F1 score} = (2\times\text{Precision}\times\text{Recall}) / (\text{Precision}+\text{Recall}) \quad (23)$$

AUC evaluates the performance of a classifier across different thresholds as indicated by the **ROC** curve. In general, the AUC value ranges from 0 to 1, which indicates a good model will have an AUC close to 1, which demonstrates a high degree of separation.

Experimental setup:

The proposed approach experiments in Google Colab using the Python language and its GPU for faster training of the model on a computer with Intel(R) Core (TM) i3-4030U CPU @ 1.90GHz, 8.00 GB RAM, and Windows 10 OS. The model is trained and tested on the ECG images dataset and its performance is evaluated based on the evaluation metrics explained above. To signify the performance of the proposed approach it is compared with models like CNN, VGG16, and ResNet50, and their performance is compared in terms of accuracy. This comparison is shown in table 4. The accuracy comparison graph of the three models with the proposed model shows that it is performing better than these models and its prediction ability for heart disease is more satisfactory.

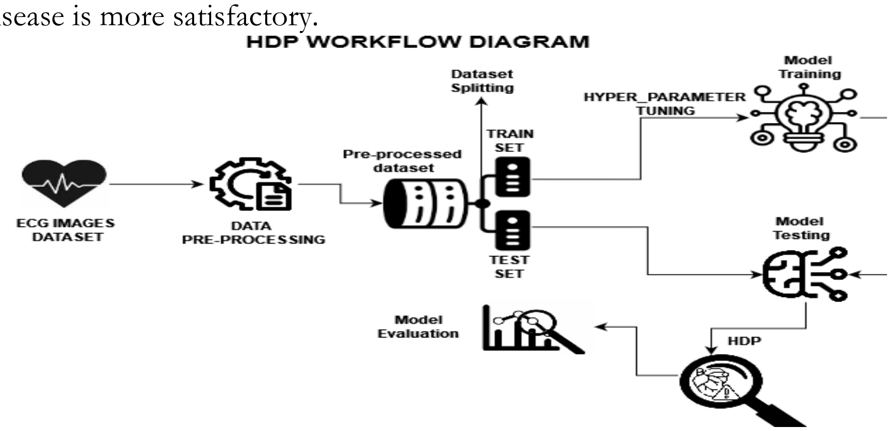

Figure 7. Workflow Diagram of proposed Heart Disease Prediction HDP Model

Results:

The results of the above experiments show that the models perform better than all the other models in terms of accuracy which is 99.8%. It means it almost correctly predicts all the ECG images into their respective four classes. The model also achieves a nearly perfect score of 0.998 in recall and F1-score across all four classes. The classification report showing the accuracy, precision, recall, and F-1 score of the ViT model for all four classes is shown in Table 3, the model achieves a perfect score in all these metrics for all four classes.

Table 3. Classification report for ViT.

	Precision	Recall	F1-Score	Support
HB	0.998	0.998	0.998	100
MI	0.998	0.998	0.998	100
PMI	0.998	0.998	0.998	100
Normal	0.998	0.998	0.998	100
Accuracy	0.998	0.998	0.998	400
Macro avg	0.998	0.998	0.998	400
Weighted avg	0.998	0.998	0.998	400

The different evaluation metrics graphs are shown in the graphs below:

Figure 8(a), shows the confusion matrix, the ViT model almost correctly classifies all the instances of all four classes and there are a few misclassified instances for all classes except the Normal class. In Figures 8(b) and 9(a), the training and validation loss and accuracy for the model are shown.

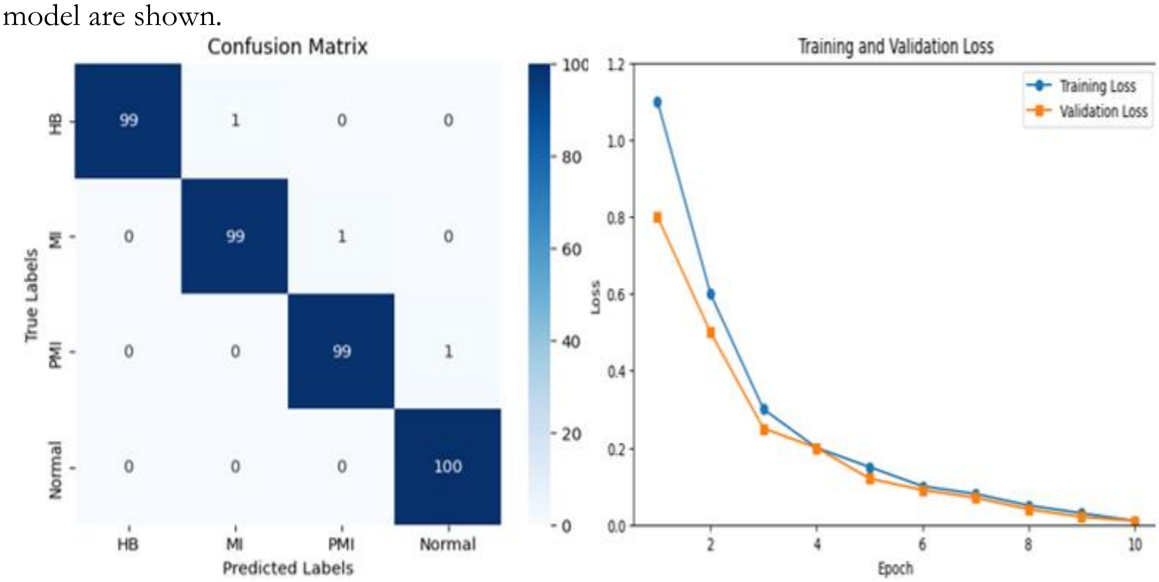

Figure 8. (a) Confusion matrix for ViT. (b) Training and validation loss for ViT.

In Figure 9(b), the Receiver operating curve (ROC curve) for the ViT model is shown. It has a value close to 1.0 (0.998) which shows that the model is working almost perfectly in classifying the images correctly in the four classes.

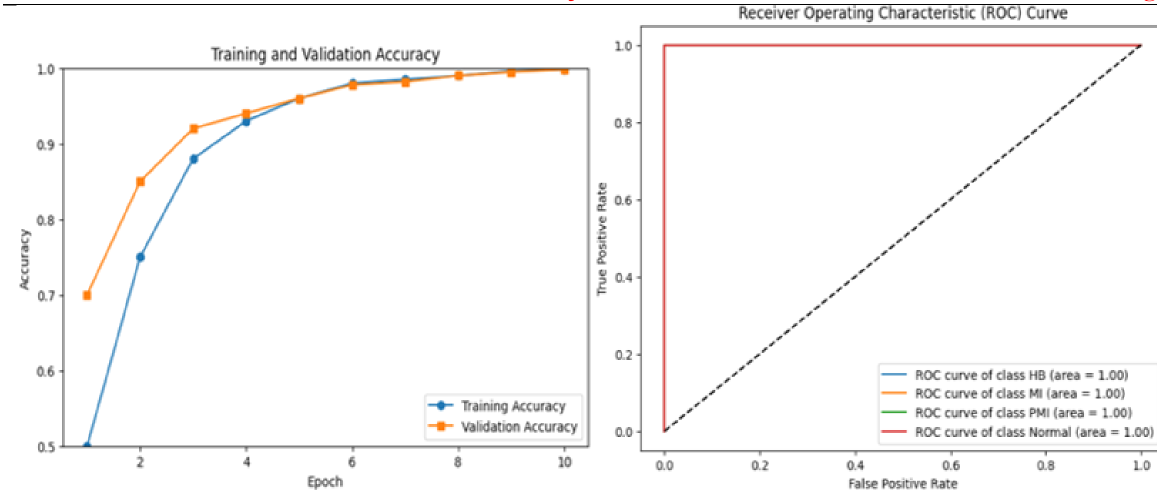

Figure 9. (a) Training and validation accuracy for ViT. (b) ROC curve for ViT.

In Figure 10(a), the F1-score for each class is demonstrated while in Figure 10(b), precision and recall are plotted against accuracy.

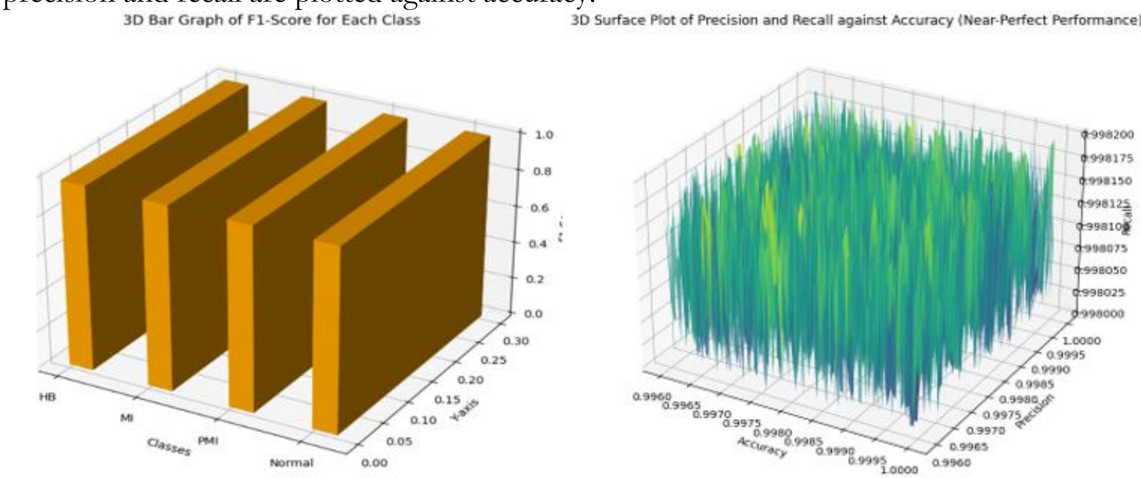

Figure 10. (a) F1-Score for each class. (b) Precision and recall against accuracy.

Figure 11(a), shows a 3D plot of the model's training and validation loss. A 3D plot of the model's accuracy, precision, and recall is shown in Figure 11(b).

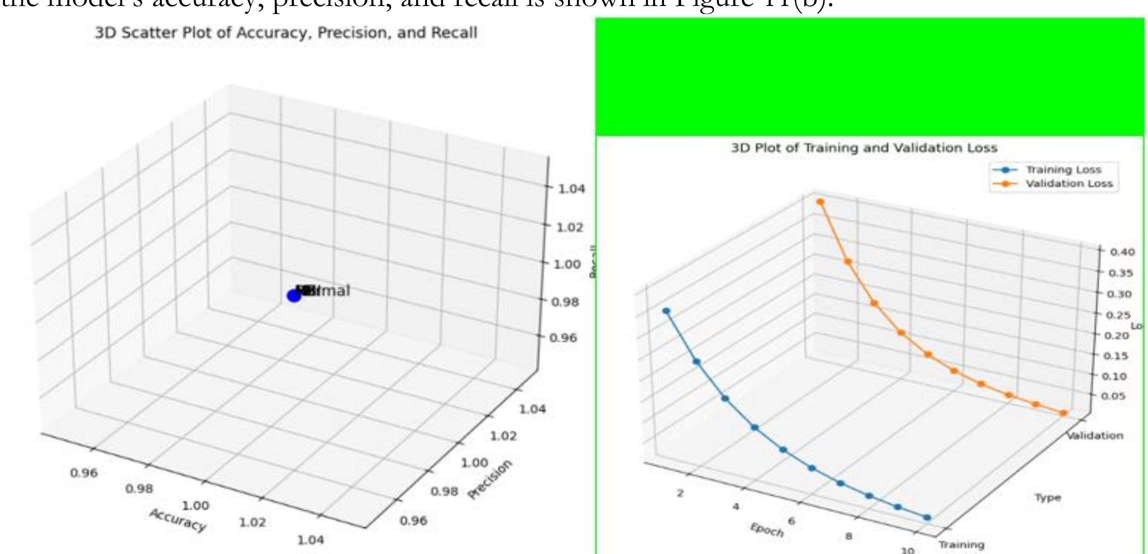

Figure 11. (a) 3D plot of training and validation loss. (b) A 3D plot of Accuracy, precision, and recall.

In Figure 12(a), the precision-recall curve to show the model's performance is presented and in Figure 12(b), the accuracy score for each class is shown. The model shows a nearly perfect accuracy of 0.998 in all the classes which shows its significance.

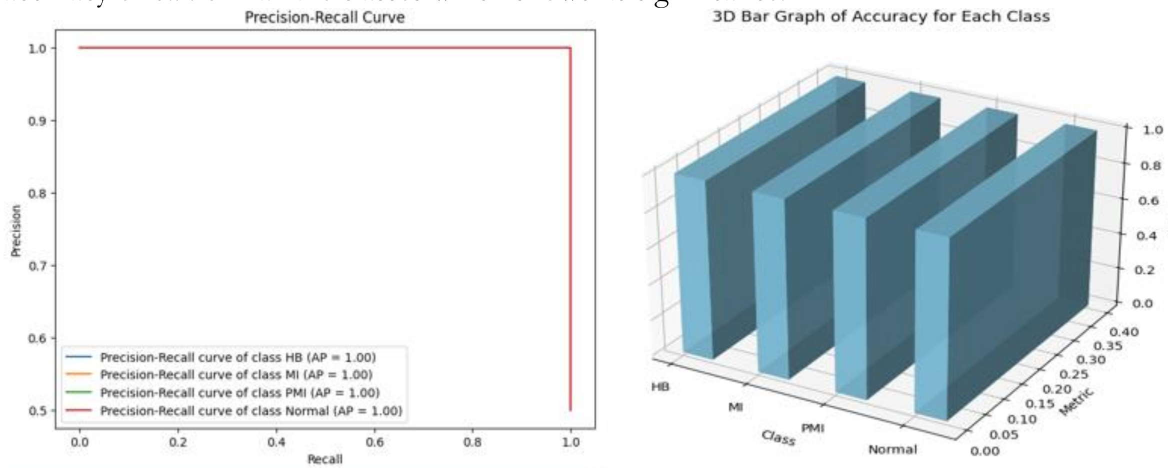

Figure 12. (a) Precision-Recall curve for ViT. (b) Accuracy for each class.

In Figure 13(a), a graph showing the accuracy, precision, recall, and F1 score for each class is shown to compare the scores for all the classes. The model achieves a nearly perfect score for these metrics for all four classes and is working amazingly. Figure 13(b), shows the training loss of the model with learning rate annotation over each epoch.

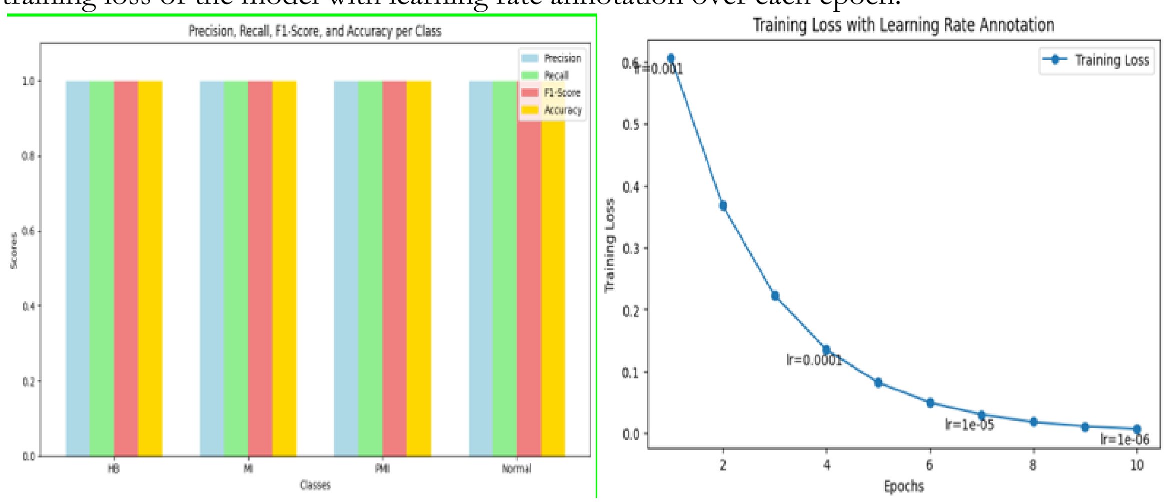

Figure 13. (a) Accuracy, Precision, Recall, and F1-score for each class. (b) Training loss with learning rate annotation.

In Figure 14(a), the confidence score distribution of the model is shown. Figure 14(b), shows the accuracy comparison of the models CNN, ResNet50, and VGG16 with our proposed ViT model. The graph shows that our model outperforms all these models with an amazing accuracy of 99.8%.

To show the significance of our model further and its enhanced generalizability capability, we have tested our proposed model by modifying our dataset a little i.e. we have induced some augmentation techniques into our dataset like rotation of images and noise injection in our image's dataset. The results of this evaluation show that the model still achieves a remarkable accuracy of 99.6% on this modified noise-induced dataset. A little lack in the model's accuracy proves that the model learns well from the diverse distributions of the data and is still able to maintain its predictive strength. The graph showing the result of this significance evaluation is shown in Figure 15.

Convolutional neural networks (CNNs) are widely used for image classification tasks and disease prediction based on electrocardiograms. CNNs employ convolutional filters, which work best with confined patterns in space, to extract features at several layers. Due to their inability to detect global contextual information and long-range dependencies, medical image analysis objectives surpass CNN's capabilities. Our approach includes a Vision Transformer (ViT) as a central component since it maintains prolonged connections between parts in ECG images by utilizing self-attention capabilities. By converting images into patch sequences, the ViT system employs a different technique than CNNs because it provides superior global representation learning over fixed receptive fields. ViT's basic architectural approach enables our model to achieve 99.6% success following data augmentation while keeping a significantly lower baseline, outperforming CNN models in terms of accuracy. ViT's improved performance demonstrates its capacity to identify hitherto unknown changes in ECG data, making it a great option for assessing heart illness using Internet of Things platforms. The architectures of both these models are shown in Figure 16.

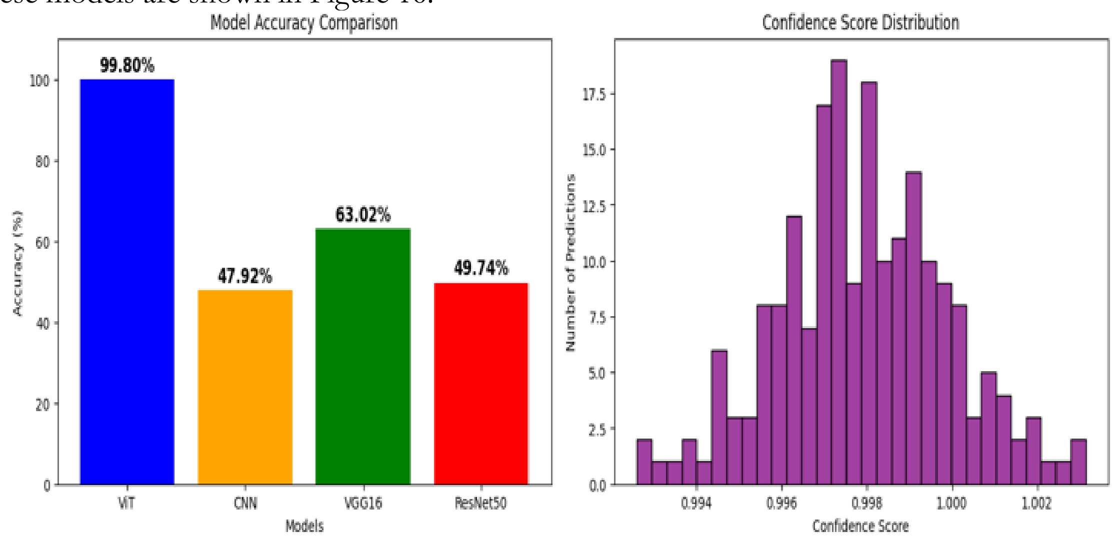

Figure 14. (a) Confidence Score Distribution for ViT. (b) Accuracy comparison of different models with the proposed model (ViT).

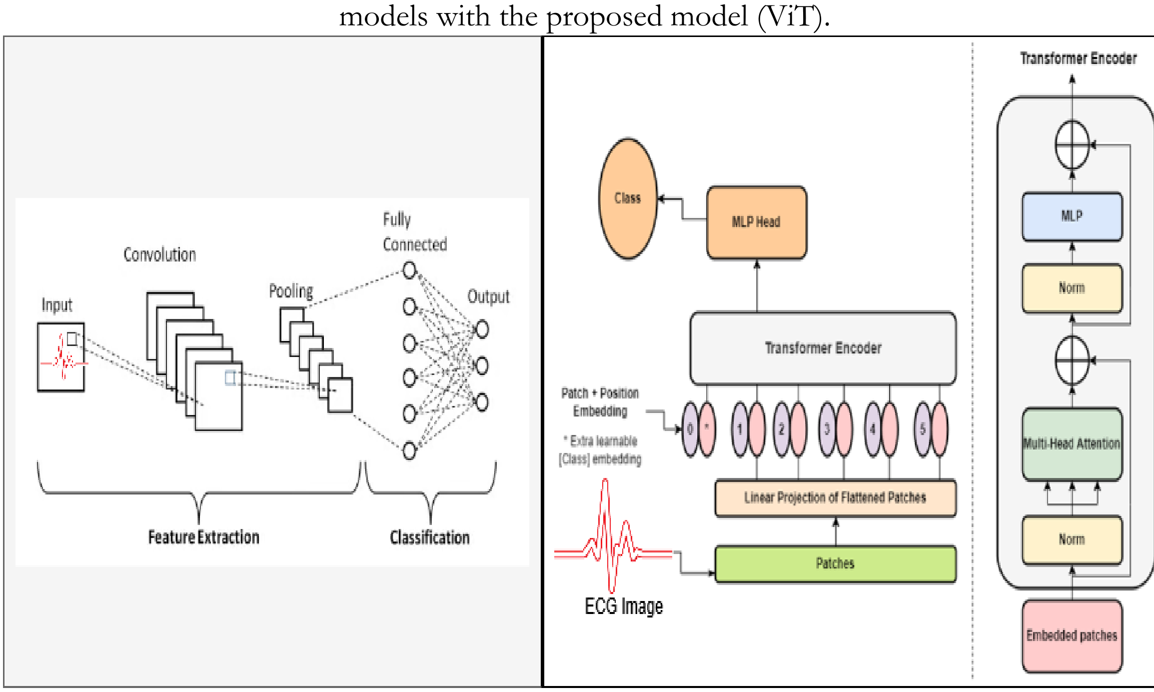

Figure 15. Comparison of architectures of CNN and proposed ViT model for HDP.

Table 4. Comparing the Accuracy of the Proposed Model with other existing models for HDP.

S.NO	Model Used	Accuracy
1	CNN	47.92%
2	VGG16	63.02%
3	ResNet50	49.74%
4	Proposed Model ViT	99.8%

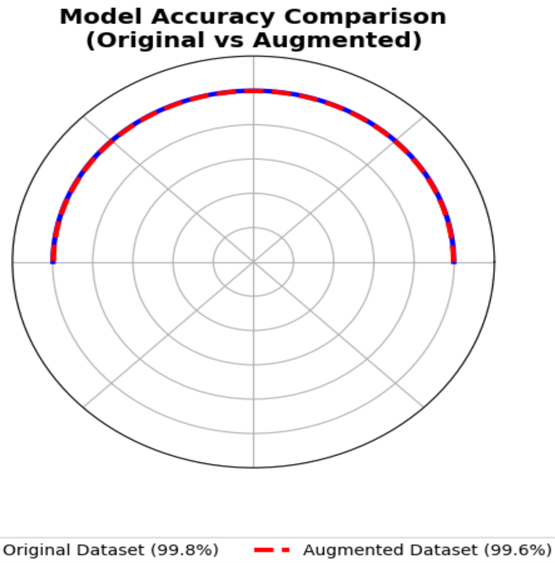

Figure 16. Comparison of accuracy of ViT for original and augmented datasets showing the significance of model showcasing effective generalization ability.

Conclusions:

This paper presents a solution based on IoT aimed at enhancing the prediction of cardiovascular diseases through early diagnosis using deep learning. Accurately identifying cardiac diseases is still a difficult task, even with improvements in clinical treatment. Our proposed Deep learning approach has proved to be a promising approach to improve diagnosis, especially in remote patient monitoring scenarios, achieving an impressive accuracy of 99.8%, Precision of 0.998, and an F1-score of 0.998. The proposed model's performance is compared with the existing state-of-the-art models like CNN, ResNet50, and VGG16 which are deployed for predicting heart disease but, our proposed approach has surpassed these all in terms of accuracy. In short, the working efficiency of the medical or healthcare field can be tremendously enhanced by our proposed approach, with accurate and on-time predictions of the disease, as well as immediate responses and precise decisions made by the medical experts that will improve the quality of the service provided as a whole and all this, is made possible by leveraging the capabilities of both IoT and the Deep learning. In future larger datasets with advanced feature selection techniques and more robust deep learning models for accurate heart disease prediction can be considered. In the future, we will also undertake the phenomena of privacy and security to protect the sensitive patient data that is being acquired from the sensors to maintain patient information integrity and confidentiality.

Acknowledgment. All authors have read and agreed to the published version of the manuscript.

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

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