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A Prediction of Heart Disease using IoT based ThingSpeak Basis and Deep Learning Method

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ABSTRACT

Developing an IoT-based system with enhanced deep learning to predict heart disease aims to revolutionize healthcare. The system, by continuously monitoring vital signs, utilizes advanced machine learning for early detection of potential heart issues, emphasizing innovation for timely interventions and potentially life-saving outcomes. Select appropriate sensors for monitoring vital signs such as heart rate, blood pressure, ECG (Electrocardiogram), oxygen saturation, and temperature. Connect these sensors to an IoT platform using wireless communication protocols like Wi-Fi. Predicting heart disease using an IoT-based ThingSpeak framework is a practical and efficient way to monitor and predict heart-related issues in real-time. ThingSpeak is an IoT platform that allows you to collect, store, analyse, and visualize data from IoT sensors. Here's a step-by-step guide on how to develop a heart disease prediction system using ThingSpeak: Deploy the trained deep learning model to make real-time predictions based on the IoT sensor data. Implement strong security regulations. The input dataset is pre-processed approach for resolving error data and missing values. On ThingSpeak, we can apply preprocessing functions to your data. This might include data smoothing, outlier removal, or missing data handling. Pre-processed data values features are then classified into normal and abnormal by Convolution Neural Network-CNN. A 10-fold cross-validation tactic was employed during the model development procedure. In the experimental result comparisons of MCC calculation, the MD2N model attained the 0.86201 and DCNN perfect reached as 0.84111 and then DBN reached as 0.91157 and then AE model rate as 0.88662 and then proposed model reaches as 0.93291 correspondingly.

1. Introduction

Chronic disease is defined as a disease that lasts for unprotracted period of time. These disorders can only be managed, not cured. The elderly are more affected than those of a younger age. Data are currently disseminated as Reports, Forms, and Statistics, among other things. They serve as inputs for a variety of approaches. Since technology is currently booming, various approaches have been

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established, and they are continuing to innovate in order to eliminate problems in every industry [1]. Technology has been extremely useful in discovering flaws in a certain industry and in resolving problems in a timely manner. This developing technology is particularly important in the field of health care. This has greatly aided in the creation of results in real-time situations. Despite this, numerous studies and researches have been undertaken in several disciplines, most notably the medical domain, which has expanded the use of technology for officially obtaining data and estimating outcomes that can be exhibited all over the world. Heart disease, commonly known as cardiovascular is a type of disease that affects the heart and blood arteries. Heart disease is classified into several categories, some of which are described below, such as myocardial infarction, sometimes known as a heart attack or angina. Coronary heart disease-CHD is another type of cardiovascular disease caused by the accumulation of a waxy material called plaque in the inner part of the coronary arteries [2]. These coronary arteries will be responsible for delivering oxygen-rich blood to the heart muscle. Atherosclerosis occurs when the waxy substance plaque begins to build up in these arteries. It is critical to receive prompt medical assistance in the event of a heart attack; this aids in preventing heart damage and preserving the patient's life. The medical professional employs modern technology to constantly monitor the data of heart patients and provide continuous guidance to the patients in order to heal from heart illness [3].

As a result, the use of data for medicine using computer technology is becoming more common. In machine learning algorithms, several feature selection strategies have been utilised. Unsupervised learning is one of them, and it is utilised for feature selection since it helps to identify the smallest subset feature that uncovers the cluster from the data based on the chosen criteria. Unsupervised feature selection eliminates the desired variable, same to how correlation eliminates redundant variables [4]. Similarly, categorization algorithms are crucial in disease prediction. A good categorization strategy will improve the suggested methodology's efficiency. It can learn non-linear models in the classification process. Furthermore, it can train models in real-time using online learning [5]. Using an IoT-based ThingSpeak framework for heart disease prediction involves leveraging ThingSpeak, an IoT platform that allows you to collect, store, analyse, and visualize data from IoT devices. Here's a more detailed guide on how to implement heart disease prediction using this approach [6]. In the realm of healthcare technology, the integration of IoT plays a pivotal role in predicting heart diseases. Key health parameters, including heart rate, blood pressure, ECG, and oxygen saturation, are monitored using sensors connected to versatile IoT devices like Raspberry Pi, Arduino, or ESP8266/ESP32. A cloud-based IoT platform, ThingSpeak, offered by MathWorks, facilitates data management and analysis. Upon setting up ThingSpeak channels for specific sensor data, the IoT device is programmed to periodically collect and transmit data using MQTT or HTTP protocols. This seamless data flow serves as the foundation for a robust heart disease prediction model, employing deep learning techniques to analyse features extracted from the sensor data. Extensive literature supports the efficacy of such IoT-based frameworks for real-time health monitoring and disease prediction [7,8].

1.1 Risk Factors of Heart Disease

The reasons for the rise in blockage are the risk factors. Gender, age, and heredity are the dimensions of non-modifiable risk factors. These risk factors are unchangeable, and they will be the primary source of heart disease. Modifiable risk variables are those that can be changed by our own efforts. Modifiable risk factors include:

i. habit-related risk factors
ii. stress-related risk factors
iii. food-related risk factors
iv. miscellaneous and biochemical risk factors.

Coronary, atherosclerosis, rheumatic, congenital, myocarditis, angina, and arrhythmia are the numerous types of heart ailments [9]. Risk factors are heart disease. Furthermore, these risk factors have the potential to worsen an already established condition. Figure 1 depicts the risk factors that impact the heart in visual style. Risk factors for cardiovascular disease include:

i. smoking
ii. a family history of heart disease
iii. hypertension
iv. cholesterol
v. diabetes
vi. obesity
vii. lack of physical activity
viii. stress

Cardiovascular disease is a broad word that various component of the heart. In medicine, the term 'cardio' refers to the meaning of the heart. As a result, all of the disorders are classified as cardiovascular disease. Risk factors such as hypertension/blood pressure, non-HDL-cholesterol, dysglycemia/diabetes, and obesity emerge as a result of a metabolic cluster that becomes powerful enough when combined with cardiovascular disease and a higher death rate than the BMI-Body Mass Index [10]. This study addresses the challenges in continuous monitoring and prediction of heart diseases, leveraging IoT technology. Specific focuses include optimizing data collection from diverse health parameters, developing efficient deep learning models for disease prediction, and addressing the modifiable and non-modifiable risk factors contributing to cardiovascular issues. The goal is to enhance real-time healthcare interventions, leveraging the potential of technology in mitigating and managing chronic heart conditions.

2. Literature Survey

The new HDPM-heart disease prediction model of (Fitriyani *et al.,* [11] has been implemented in an effective manner for clinical decision support system supported with DBSCAN-Density based spatial clustering of Applications with noise and with the help of SMOTE-ENN technique, to detect the heart disease by balancing the data trained and XGBoost. Two separate datasets, statlog and Cleveland, were used, and their results are described in conjunction with various models like as LR (Logistic Regression), Navies Bayes -NB, Decision tree-DT, Multilayer preceptor-MLP, SVM-Support Vector Machine, and previous study results. Using these two models, the results inferred from this study have acquired accuracies of 95.90% for statlog dataset and 96.40% for Cleveland dataset. Additionally, the Clinical Decision Support System (CDSS) is integrated with this model to display the patient's current position. To improve this study, a specific dataset was collected from a specific place, and a heart specialist was consulted to validate the presented predicted model, as well as the dataset that was utilised to validate the result achieved.

A variety of classifiers are used to predict cardiovascular disease. Nayak *et al.,* [12] predicted the early stage of heart disease using several classification approaches such as Navies Bayes, classifier, and k-NN classifiers. They are used to detect early stages of disease and to prevent it. The accuracy attained by Navies Bayes is better than the other classification algorithms when assessing several techniques for diagnosing heart disease at the early stage of its unhealthiest. After better filtration, this technique was integrated in the R data analytics tool for diagnosing cardiovascular disease. As part of the upgrade, higher accuracy will be achieved by ensemble machine learning.

Maji *et al.,* [13] describe the decision tree algorithm as a classification method that can be utilised for the prediction of cardiovascular disorders. The hybridization method has been implemented in this methodology by merging the decision tree and artificial neural network as a single technique to improve prediction of heart illnesses using WEKA. This performance was evaluated using a tenfold assessment test, and it is useful for analysing the heart disease patient dataset from the UCI dataset. Accuracy, specificity, and sensitivity are performance indicators calculated for both hybrid and individual classifier approaches. These various combinational strategies are introduced to forecast cardiac illness and help clinical personnel discover many types of ailments in the early stages. The results of the hybridization techniques reveal that the suggested technique outperforms the individual strategy and produces good results for heart disease prediction. Various data mining approaches can be employed in the enhancement to forecast various types of diseases sooner.

In general, classifiers are employed in machine learning approaches to deliver a person's faults, and they are introduced for forecasting heart problems by analysing different indicators such as HbA1c, cholesterol level, ECG readings, and heart rate. Kumar *et al.,* [14] assessed several machine learning algorithms and classifiers based on accuracy rate and computation time over the prediction of heart disease datasets to identify heart disorders. LMT-Logistic Model Trees, Random Forest, J48, Random Tree classifiers, and Hoeffding tree are the classifiers used to identify cardiac disorders. Following the end of the investigation, the results produced by the analysed datasets conclude that the Hoeffding tree has a greater accuracy of 85.1852 percent than the other classifiers and a computation time of 0.17s for predicting the heart disease patient.

Alsaeedi *et al.,* [15] employed the PSO-particle swarm optimisation technique to increase the performance of the ANN. The majority of the non-linear models have been solved and analysed using a combination of Artificial Neural Network and PSO techniques. For optimising the performance of the ANN network, the HNN-Heuristic Optimisation model was employed in conjunction with the artificial neural network. The proposed technique is used in conjunction with PSO to determine the ANN's minimum weight for replacing back propagation procedures. The recorded result is aimed to obtain less processing time (76.91 sec on average) than the backpropagation algorithm (93.32 sec on average).Furthermore, the proposed technique has a higher accuracy rate of 95.8 percent than the backpropagation algorithm, which has an accuracy rate of 85.4 percent.

According to Saini *et al.,* [16] numerous authors have proposed several techniques that have greatly aided the medical professions by focusing primarily on the protection of human life. Despite the fact that numerous approaches have been adopted, there are various problems due to an incorrect heart and body figure. Nowadays, the use of machine learning procedures, primarily in the health profession, has greatly aided medical practitioners in the protection of human life. The authors examined a hybrid prediction strategy for the diagnosis of cardiac disorders utilising SMO and ANN methodologies. This new strategy exceeded the previous procedures by increasing the accuracy rate in predicting heart disease to 95.4 percent, which is considered to be the highest among the other standard methods. The authors' advice for improving accuracy is to use a large number of datasets with the inclusion of multiple feature selection algorithms.

3. Problem Identification

In general, data mining is one of the booming technologies, and it is relevant in a variety of industries that are on the rise. Data mining techniques are used in e-commerce, retail, and a variety of other areas. These data mining approaches are currently being used in the health care industry to predict or diagnose various diseases in their early stages. Data mining techniques include data pre-processing, feature extraction, and classification algorithms that can be used to forecast cardiac disease.

4. Proposed Methodologies

To monitor and forecast heart-related issues in real-time, we are using an IoT-based ThingSpeak framework in this proposed system. You can collect, store, analyse, and visualise data from IoT sensors using the IoT platform ThingSpeak. Here is a step-by-step tutorial for creating a ThingSpeak heart disease prediction system: Use the deep learning model you've trained to make immediate predictions based on data from IoT sensors. Put in place strict security rules. Pre-processing is used to deal with error data and missing values in the input dataset. We can perform preprocessing on your data on ThingSpeak. This could involve handling missing data, outlier removal, or data smoothing. Convolution Neural Network-CNN then divides the pre-processed data values and features into normal and abnormal categories [17]. During the model development process, a 10-fold cross-validation strategy was used.

4.1 Data Preprocessing

The amount of data utilised for training determines how well the model performs. Preprocessing is done on the photos to help the model run more efficiently. In examples of brain tumour images with axial, coronal, and sagittal orientations. The photographs have been scaled down to 100 * 100 and put into the grayscale format. In an 80:20 ratio, the dataset is divided into sets. For training deep neural networks in our proposed work, a limited dataset was used. Therefore, we used data augmentation techniques including flipping the data horizontally and vertically, rotating it, shifting it, zooming it, and correcting the brightness, which improved the suggested models' accuracy [18].

4.2 Classification Techniques

The basic and major principle in data mining approaches is the wiser use of classifiers, followed by illness prediction.

Classification in data mining is the process of discovering the model set that characterises and differentiates the classes of data or concepts. The classification algorithm is the most commonly used algorithm in learning.

Fig. 1. The structure of classification model

Machine learning techniques are generally classified into three types based on their learning style: unsupervised learning, supervised learning, and reinforcement learning. The classification algorithm is a method of learning in which the machine learns how to give labels to each data class. There are several classification algorithm strategies, including Naive Bayes, Logistic Regression, decision trees, random forests, linear perceptron, and gradient-boosted trees.

4.3 Convolution Neural Network

A CNN is used for image classification and computer vision tasks. 10-fold cross-validation is a robust procedure for assessing the performance of your CNN model, especially when dealing with limited datasets. It helps in assessing the model's generalization and reducing the risk of overfitting. Here's how to implement a 10-fold cross-validation approach for training and evaluating your CNN model. You may want to use the full dataset for training the final model using the hyperparameters and model architecture determined through cross-validation. By following this 10-fold cross-validation approach, you can effectively assess the performance of your CNN model while maximizing the utilization of your available data and minimizing the risk of overfitting. Adjust the model architecture and hyperparameters based on the cross-validation results to improve its performance.

Test the final model on a separate validation or test set that was not used during cross-validation to estimate its real-world performance. Convolution Neural Network-CNN is a Neural Network that is meant to analyse multidimensional data such as time series data and images. CNN has the ability to discover patterns and make sense of them; this pattern detection allows CNN to be used for picture analysis. CNN is useful for making better predictions with large datasets while minimising the number of parameters and training quantity.

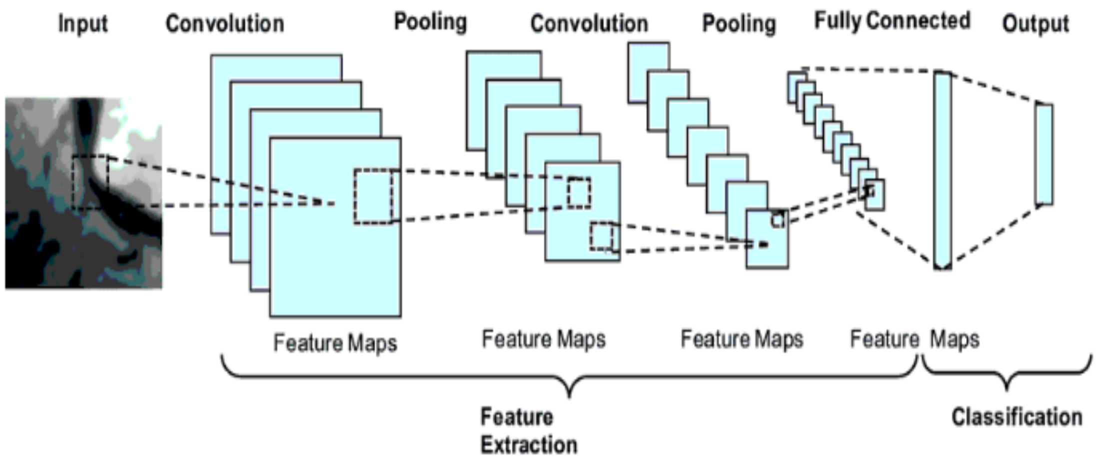

Fig. 2. Typical architecture of convolution neural network

A (CNN) tasks involving visual data, particularly image recognition and classification. CNNs have achieved remarkable success in computer vision, image analysis, and related fields. They are characterized by their ability to mechanically learn and extract making them highly effective for tasks like object recognition, face detection, and more [19]. Here are some key aspects of CNNs.

There is free communication between neurons in different levels, but communication between neurons in the same layer is inhibited. Here, we can see the surrounding visible layer shown as:

$$vis = \{vis_1, vis_2, \dots, vis_j, \dots, vis_m\};\ (vis_j \in \{0,1\}) \quad (1)$$

Likewise, any one of the hidden layers employed in DBN is expressed as

$$hid = \left\{hid_1, hid_2, \dots, hid_j, \dots, hid_m\right\};\ \left(hid_j \in \{0,1\}\right) \quad (2)$$

Visible layers are indicated by the vis notation, whereas hidden layers are stated as hid. The suggested CN technique determines the number of layers based on the input pre-processed result N(y,z). These characteristics with their standard deviations modified are transmitted to the visible layer, which may then transmit them to the hidden layer. Instead of sharing a direct connection, neurons on separate levels are instead coupled via a weight relationship. The first three parameters of this design are =W,b,c>>. W denotes the weight matrix, B the bias in the hidden layer, and C the bias in the top layer. Where vis j indicates the visible unit in the jth layer and hid j denotes the hidden unit in the jth layer, the proposed RBM architecture consists of n hidden neurons and m input neurons. This parameter structure is expressed mathematically as follows:

$$W = \left\{w_{j,k} \epsilon S^{m \times n}\right\} \quad (3)$$

Here $w_{j,k}$indicates weight value of neuron in j^{th} layer and k^{th} layer. The bias function of hidden layer B is exactly uttered as shadows.

$$B = \left\{b_j \epsilon S^n\right\} \quad (4)$$

The b_j term in the preceding equation represents a cutoff value for the hidden neuron's bias function at the jth position in the hidden layer. The same method is used to determine the bias function for the optical layer.

$$C = \{c_k \epsilon S^m\} \quad (5)$$

The variable c k in the above equation stands for the bias function's threshold value for the kth observable neuron in the layer. Between the RBM's hidden and output layers, the energy function is used to learn probability functions. By solving the following equation for the energy function, we obtain the distribution of probabilities:

$$E(vis, hid|\theta) = -\sum_{j=1}^{m} b_j vis_j - \sum_{k=1}^{n} c_k hid_k - \sum_{j=1}^{m}\sum_{k=1}^{n} vis_j W_{jk} hid_k \quad (6)$$

Here $\theta = \left\{W_{jk}, b_j, c_k\right\}$ consist of the parameters of the RBM model and the E term, which defines the energy function between the hidden and visible nodes. The total sum of visible neurons is equal to m plus the sum of hidden neurons is equal to n.

After accounting for the exponential and regularisation of the energy function, the probability function may be defined. Here is a formula for the overlap between the probabilities of the RBM model's open and hidden layers:

.

$$P(vis, hid|\theta) = \frac{1}{Z(\theta)} e^{-E(vis,hid|\theta)} \quad (7)$$

The Gibbs distribution function of the RBM model provides the basis for this equation. The partition function may be calculated from this equation.:

$$Z(\theta) = \sum_{vis,hid} e^{-E(vis,hid|\theta)} \tag{8}$$

Here $Z(\theta)$ It refers to a function that is either uniformly distributed or normalised, and that represents the total energy state of all layers, including those that are visible and those that are not. It is the sum of the energy evaluations done on the two layers (the visible and the concealed). A probability function can be used to regulate the standards of the parameters. Here, the notation serves as the fundamental device for expressing the joint distribution of the visible and hidden layers, denoted by P(vis,hid|). In this case, P(vis|) is meant to represent the marginal distribution function of the visible layer, and it may be mathematically labelled as such:

$$P(vis|\theta) = \frac{1}{Z(\theta)} \sum_{hid} e^{-E(vis,hid|\theta)} \tag{9}$$

We may evaluate the aforementioned marginal layer by summarising the criteria of the entire network. In order to calculate the marginal distribution function of the hidden layer, we utilise the following equation:

$$P(hid|\theta) = \frac{1}{Z(\theta)} \sum_{vis} e^{-E(vis,hid|\theta)} \tag{10}$$

The exponential form of the RBM design allows for connections both between and within its levels. Conditional probability values in RBM may be determined using the following formulae since its disclosed and concealed layers are independent.

$$P(vis|hid) = \prod_j P\left(vis_j|hid\right) \tag{11}$$

$$P(hid|vis) = \prod_k P(hid_k|vis) \tag{12}$$

As will be seen below, a sigmoid activation function is appropriate for use with the proposed RBM architecture since its parts are in a binary state.

$$sigmoid(y) = \frac{1}{(1+e^{-y})} \tag{13}$$

Using this activation function as a basis, we can write down the probabilities for the RBM structure's visible and hidden layers as follows.

$$sigmoid(y) = \frac{1}{(1+e^{-y})} \tag{14}$$

$$P\left(vis_j = 1|hid\right) = \frac{1}{1+exp\left(-b_j - \sum_{k=1}^{n} w_{jk} hid_k\right)} \tag{15}$$

$$P(hid_k = 1|vis) = \frac{1}{1+exp\left(-c_k - \sum_{j=1}^{m} w_{jk} vis_j\right)} \tag{16}$$

The next stage of the suggested classification framework is to update the rules for the relevant parameters =W,b,c. The Gibbs distribution function of the RBM model is not always immediately applicable. As a result, we advocate for the employment of a fast-learning method known as Contrast Divergence (CD) to cut down on the amount of time spent on such endeavours. The updated parameter values based on the aforementioned method of learning are presented quantitatively in the following equations.

$$W^{time+1} = W^{time} + \varepsilon\left(P\left(hid|vis^{(0)}\right)\left[vis^{(0)}\right]^{time} - P\left(hid|vis^{(1)}\right)\left[vis^{(1)}\right]^{time}\right) \tag{17}$$

$$b^{time+1} = b^{time} + \varepsilon\left(vis^{(0)} - vis^{(1)}\right) \tag{18}$$

$$c^{time+1} = c^{time} + \varepsilon\left(P\left(hid|vis^{(0)}\right) - P\left(vis^{(1)}\right)\right) \tag{19}$$

Here, time represents the size of the learning steps iteratively. Until the parameter values have been adjusted to provide a feature representation that is both more abstract and more representable than the one generated by the bottom layer, the preceding processes are repeated. The suggested model used the aforementioned equations to achieve its aim of feature extraction [20]. The coot optimisation procedure's training method allows the suggested change detection model to avoid specialised capabilities. A more sophisticated collection of features is produced overall, which aids the effectiveness of the detecting system.

i. **Convolutional Layers:** The fundamental building blocks of CNNs are convolutional layers. These layers apply convolution operations to the input image. The convolution operation involves sliding a small patterns and features. This process allows the network to learn different levels of abstraction, starting from simple edges and shapes to complex objects.
ii. **Pooling Layers:** After convolutional layers, CNNs often include pooling layers while plummeting computational difficulty.
iii. **Fully Connected Layers:** Following the CNNs typically have one or more fully connected layers. These layers are similar to those in traditional neural networks, and they help in making final decisions and predictions.
iv. **Activation Functions:** Each neuron in a CNN typically uses an activation function (e.g., ReLU - Rectified Linear Unit) to present non-linearity and allow the network to learn complex patterns.
v. **Feature Learning:** CNNs automatically learn to recognize features by training on labelled datasets. The convolutional layers combine these features to make predictions.
vi. **Weight Sharing:** One key advantage of CNNs is weight sharing. Convolutional layers use the same set of learned weights for different regions of the input image, which helps in capturing translational invariance, making the model robust to slight changes in the object's position.
vii. **Data Augmentation:** Data augmentation procedures, such as rotation, flipping, and cropping, are often used to artificially increase dataset, improving the model's generalization.
viii. **Transfer Learning:** CNNs can benefit from transfer learning, where a pre-trained model (e.g., VGG, ResNet, or Inception) is fine-tuned on a new task. This approach is especially useful when you have a limited amount of labelled data.
ix. **Loss Functions:** The choice of a loss function depends on the task you're trying to solve. Common loss functions for classification tasks include SoftMax cross-entropy, while regression tasks may use mean squared error.
x. **Regularization:** To avert overfitting, regularization procedures like dropout and L2 regularization can be applied to the fully connected layers of the CNN.

xi. **Optimization Algorithms:** Optimization algorithms such as variants, like Adam, are used to training.

xii. **Batch Normalization:** Batch normalization is a technique that normalizes the output of each layer to have zero mean and unit variance, improving training stability and convergence.

CNNs have applications in various domains, including image classification, object finding, image segmentation, facial recognition, medical image analysis, autonomous vehicles, and more. They have significantly progressive the field of endure to be a key technology in the development of AI and machine learning systems [21].

5. Results and Discussion

In our experimental analysis, conducted on an Intel(R) Core (TM) i5-7200u, 2.50–2.7 GHz CPU, with 16 GB RAM and an 8 GB graphics card, we applied the proposed method for heart disease prediction. The evaluation metrics, including Jaccard and Dice similarity coefficients (JSC and DSC), along with TP, FP, FN rates, and TN set characterization, were employed. The experimental setup and data sources, coupled with the proposed method, contribute to the significance of our achieved metrics in predicting heart disease.

5.1 Experiment on Classification Results

Some presentation metrics are projected for assessing the presentation.

i. Accuracy: “ratio of the observation of exactly predicted to the whole observations”.

$$T^{accuracy} = \frac{(Tr^p + Tr^n)}{(Tr^p + Tr^n + Fa^p + Fa^n)} \tag{20}$$

ii. Sensitivity: “the number of true positives, which are recognized exactly”.

$$Se = \frac{Tr^p}{Tr^p + Fa^n} \tag{21}$$

iii. Specificity: “the number of true negatives, which are determined precisely”.

$$sp = \frac{Tr^n}{Fa^n} \tag{22}$$

iv. Precision: “the ratio of positive observations that are predicted exactly to the total number of observations that are positively predicted”.

$$Pr = \frac{Tr^p}{Tr^p + Tr^p} \tag{23}$$

v. FPR: “the ratio of count of false positive predictions to the entire count of negative predictions”.

$$FPR = \frac{Fa^P}{Fa^P + Tr^n} \tag{24}$$

vi. FNR: “the proportion of positives which yield negative test outcomes with the test”.

$$FNR = \frac{Fa^n}{Tr^n + Tr^p} \tag{25}$$

vii. NPV: “probability that subjects with a negative screening test truly don’t have the disease”.

$$NPV = \frac{Fa^n}{Fa^n + Tr^n} \tag{26}$$

viii. FDR: “the number of false positives in all of the rejected hypotheses”.

$$FDR = \frac{Fa^p}{Fa^p + Tr^p} \tag{27}$$

ix. F1 score: It is distinct as the “harmonic mean between precision and recall. It is used as a statistical measure to rate performance”.

$$F1score = \frac{Se.Pr}{Pr + Se} \tag{28}$$

x. MCC: It is a “correlation coefficient computed by four values”.

$$MCC = \frac{Tr^p \times Tr^n - Fa^p \times Fa^n}{\sqrt{(Tr^p + Fa^p)(Tr^p + Fa^n)(Tr^n + Fa^p)(Tr^p + Fa^n)}} \tag{29}$$

Table 1 provides a summary of the classifier's performance on a number of different measures. In the study, the best implementation of the Decision Tree Classifier achieved a 0.983 accuracy in testing, 1.0 accuracy in training, 0.98 precision, 0.98 recall range, and 0.98 F1-score. Testing accuracy for the final CatBoost classifier was 0.975, accuracy was 0.98, precision was 0.98, recall range was 0.97, and the F1-score was 0.97. The KNN was then shown to be flawless, with a testing accuracy of 0.975, a accuracy of 0.985, a precision of 0.97, a recall range of 0.97, and an F1-score of 0.97. Finally, the F1-score for the Random Forest classifier was 0.59, as was the testing accuracy, the accuracy, the precision, the recall range, and the F1-score. Next, the Naive Bayes classifier accomplished a flawless testing accuracy of 0.975, followed by a training accuracy of 0.99 within a range of 0.97, and an F1-score of 0.97. After reaching a accuracy of 0.89, recall range of 0.88, and F1-score of 0.88, the Gradient boosting classifier was considered to be near-perfect. The LGBM classifier was then flawless, with a testing accuracy of 0.975, a training accuracy of 1.098, a precision of 0.97, and an F1-score of 0.97. The Extra tree classifier achieved a flawless F1-score of 0.975, precision of 0.98, recall within a range of 0.97, and accuracy of 0.975, 0.98, and 1.0 during training. Then, the SVM achieved a correctness of 0.983, a training of 0.98, recall within a range of 0.98, and an F1-score of 0.98. After reaching training accuracy of 1.0, testing accuracy of 0.9833, precision of 0.98, recall range of 0.98, and F1-score of 0.98, the ANN classifier was considered to be flawless. After that, we have ResNet at 0.9666, accuracy at 0.97, recall range at 0.97, then F1-score at 0.97. Thereafter, the AlexNet achieved a challenging accuracy of 0.6, an accuracy of 0.36, a recall range of 0.60, and an F1-score as 0.45. Afterward attainment a training accuracy of 0.978, a testing accuracy of 0.958, and an F1-score as 0.96, the VGGNet was considered to be near-perfect. The proposed classifier reached an F1-scoree of 0.99 after achieving an accuracy of 0.9916 in testing, 0.946% in training, 0.946% to 0.99% in recall, and 0.99% to 99% in F1-score.

Table 1
Investigation of classifier on numerous systems of measurement

Classifiers	F1-score	Training accuracy	Testing accuracy	Precision	Recall
Decision tree	0.98	1.0	0.983	0.98	0.98
CatBoost	0.97	0.98	0.975	0.98	0.97
Random forest	0.59	0.76	0.59	0.58	0.59
ANN	0.98	1.0	0.9833	0.98	0.98
ResNet	0.97	0.946	0.9666	0.97	0.97
Naïve Bayes	0.97	0.99	0.975	0.98	0.97
Gradient boosting	0.88	0.9	0.8833	0.89	0.88
LGBM	0.97	1.0	0.975	0.98	0.97
Extra tree	0.97	1.0	0.975	0.98	0.97
SVM	0.98	1.0	0.983	0.98	0.98
AlexNet	0.45	0.6357	0.6	0.36	0.60
Projected Model	0.99	1.0	0.9916	0.99	0.99

In above Table 2 represent that the Classifier Analysis on Dataset 1. In Accuracy calculation, the MD2N model attained the 0.92969 and DCNN perfect reached as 0.91927 and then DBN reached as 0.95573 and then AE model rate as 0.94271 and then DBN-COA model reaches as 0.96615 correspondingly. Then the Sensitivity calculation, the MD2N model attained the 0.89063 and DCNN perfect reached as 0.88021 and then DBN reached as 0.94792 and then AE model rate as 0.91667 and then DBN-COA model reaches as 0.94792 correspondingly. Then the Specificity calculation, the MD2N model attained the 0.96875 and DCNN perfect reached as 0.95833 and then DBN reached as 0.96354 and then AE model rate as 0.96875 and then DBN-COA model reaches as 0.98438 correspondingly. Then the Precision calculation, the MD2N model attained the 0.9661 and DCNN perfect reached as 0.9548 and then DBN-COA model reaches as 0.96296 and then DBN reached as 0.96703 and then AE model rate as and then DBN-COA model reaches as 0.98378 correspondingly. Then the FPR calculation, the MD2N model attained the 0.03125 and DCNN perfect reached as 0.041667 and then DBN reached as 0.036458 and then AE model rate as 0.03125 and then DBN-COA model reaches as 0.015625 correspondingly. Then the FNR calculation, the MD2N model attained the 0.10938 and DCNN perfect reached as 0.11979 and then DBN reached as 0.052083 and then AE model rate as 0.083333 and then DBN-COA model reaches as 0.052083 correspondingly. Then the NPV calculation, the MD2N model attained the 0.96875 and DCNN perfect reached as 0.95833 and then DBN reached as 0.96354 and then AE model rate as 0.96875 and then DBN-COA model reaches as 0.98438 correspondingly. Then the FDR calculation, the MD2N model attained the 0.033898 and DCNN perfect reached as 0.045198 and then DBN reached as 0.037037 and then AE model rate as 0.032967 and then DBN-COA model reaches as 0.016216 correspondingly. Then the F1-Score calculation, the MD2N model attained the 0.92683 and DCNN perfect reached as 0.91599 and then DBN reached as 0.95538 and then AE model rate as 0.94118 and then DBN-COA model reaches as 0.96552 correspondingly. Then the MCC calculation, the MD2N model attained the 0.86201 and DCNN perfect reached as 0.84111 and then DBN reached as 0.91157 and then AE model rate as 0.88662 and then proposed model reaches as 0.93291 correspondingly.

Table 2
Classifier Analysis on Dataset 1

Measures	MD2N	DCNN	DBN	AE	projected
Accuracy	0.92969	0.91927	0.95573	0.94271	0.965
Sensitivity	0.89063	0.88021	0.94792	0.91667	0.942
Specificity	0.96875	0.95833	0.96354	0.96875	0.988
Precision	0.9661	0.9548	0.96296	0.96703	0.988
FPR	0.03125	0.041667	0.036458	0.03125	0.0155
FNR	0.10938	0.11979	0.052083	0.083333	0.0523
NPV	0.96875	0.95833	0.96354	0.96875	0.988
FDR	0.033898	0.045198	0.037037	0.032967	0.0116
F1-Score	0.92683	0.91599	0.95538	0.94118	0.9652
MCC	0.86201	0.84111	0.91157	0.88662	0.9321

6. Conclusion

In conclusion, the proposed IoT-based framework coupled with an enhanced deep learning approach presents a ground breaking solution for predicting heart disease, demonstrating its potential for continuous vital sign monitoring and early detection of cardiac issues. The experimental results, particularly the Matthews Correlation Coefficient (MCC) calculations, showcase the efficacy of different models, with the proposed model attaining an impressive MCC of 0.93291. This underscores the system's accuracy in distinguishing between normal and abnormal conditions. The selection of appropriate sensors and the utilization of ThingSpeak as an IoT platform contribute to the system's practicality and efficiency in real-time heart disease prediction. Despite these achievements, it is essential to acknowledge certain limitations. The study primarily focused on specific numerical metrics, and additional evaluation criteria could further enhance the comprehensiveness of the assessment. Additionally, stringent security measures were emphasized, but the study recognizes the evolving landscape of cybersecurity, necessitating ongoing efforts to adapt to emerging threats. Future work should explore expanding the dataset diversity and incorporating more advanced preprocessing techniques to bolster the model's robustness. Furthermore, investigations into the integration of additional health parameters and the enhancement of real-time prediction capabilities could further elevate the system's utility in clinical settings.

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