An Integrated Accurate-Secure Heart Disease Prediction (IAS) Model using Cryptographic and Machine Learning Methods

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Abstract

Heart disease is becoming the top reason of death all around the world. Diagnosing cardiac illness is a difficult endeavor that necessitates both expertise and extensive knowledge. Machine learning (ML) is becoming gradually more important in the medical field. Most of the works have concentrated on the prediction of cardiac disease, however the precision of the results is minimal, and data integrity is uncertain. To solve these difficulties, this research creates an Integrated Accurate-Secure Heart Disease Prediction (IAS) Model based on Deep Convolutional Neural Networks. Heart-related medical data is collected and pre-processed. Secondly, feature extraction is processed with two factors, from signals and acquired data, which are further trained for classification. The Deep Convolutional Neural Networks (DCNN) is used to categorize received sensor data as normal or abnormal. Furthermore, the results are safeguarded by implementing an integrity validation mechanism based on the hash algorithm. The system's performance is evaluated by comparing the proposed to existing models. The results explain that the proposed model-based cardiac disease diagnosis model surpasses previous techniques. The proposed method demonstrates that it attains accuracy of 98.5 % for the maximum amount of records, which is higher than available classifiers.

Keywords: Heart Disease Prediction, accuracy, integrity, Machine learning, feature extraction, Neural networks

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1. Introduction

As reported in World Health Organization (WHO), cardiac disorders account for the vast majority of deaths globally. It is feasible to estimate that cardiac illnesses account for around 30% of all deaths [1] [2]. As a result, strategies for recognizing early indicators of cardiac disease are critical for guaranteeing global well-being. At this stage, due to the great variety of medical scenarios, as well as the actuality that perhaps the diseases and related indications cover such a broad range, it is often a complex work to properly evaluate the inputs. Biomedical-based decision making models have been utilized to extract accurate data from target information in aim of assisting doctors in their diagnosis process [3] [4]. At this instant, the commonly used process inside decision support systems is categorization, which allows for an accurate decision-making method by assessing preexisting information and conduct comparisons over it. In the context of study has been planned, researchers are continually striving to improve classification success rates. To accomplish this, they typically create several types of classification models. Recently, the technological period has risen over numerous creative solutions, including the Internet of Things (IoT), which is recognized as a communication model using smart gadgets [5, 6]. As IoT has grown in popularity in several spheres of present days, attempts in the biomedical perspective have resulted in the emergence of a distinct name: the Internet of Health Things (IoHT)

The healthcare business was quick to adopt IoT [7], [8], as integrating IoT features into clinical devices progresses service quality and efficiency. This importantly helps for the senior citizens, patients with heart diseases, and persons who require consistent supervision [9]. IoT-based health-based apps are used to collect critical data, such as concurrent differences in health factors and data on the severity of clinical factors within a set time period, so IoT devices continuously generate massive clinical records. The IoT is widely regarded as the vital advanced technology, and it is obtaining traction in the medical industry [10].

The IoT has been shown to have significant promise in riskier environment, health, and safety domains, where life of persons are in danger, and IoT-based services are poised to provide protected, trustworthy, and valuable solutions. Individuals, who require obtaining data about their medical conditions, including pulse rate, BP, and glucose level, can benefit from smart wearable devices. This information can be continuously monitored and delivered to cellphones via sensors on wearable equipment [11]. Electrocardiogram (ECG) sensors are connected to the IoT, which is supported by plug-and-play capability. The collected data is kept in the remote server using IoT systems. Hence, both current and previous patient information can be viewed from a remote location. Healthcare monitoring should be ongoing in order to track the patient's physiological characteristics and provide consistent and reliable data to doctors or medical teams for disease detection. Pulse rate, BP, BMI, glucose level, and ECG are importantly considered for monitoring functions.

ML is utilized in a variety of services, ranging from detection of risk metrics to building sophisticated protection models for autos. Providing solution for the current issues, ML gives dominating predictive modelling techniques [12]. It contains the source for converting enormous data for the development of prediction algorithms. It is based on a computer learning intricate and non-linear associations among qualities by dropping the dissimilarity between actual and the obtained values [13]. The model is pre-trained with features obtained from datasets. Classification is an important ML method that, when trained with proper data, is successful for identifying illness [14]. The general model for heart disease diagnosis is presented in **Fig. 1**.

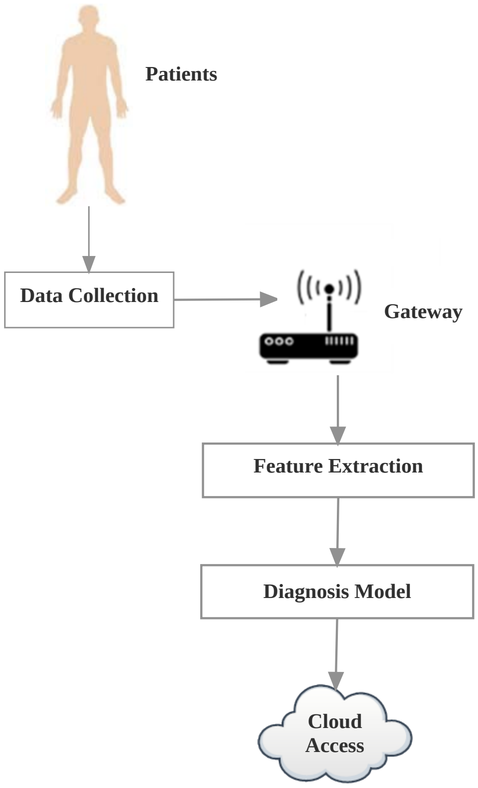

Fig. 1. General Model for Heart Disease Diagnosis

The primary contribution of this study is the development of an intelligible clinical disease prediction model for the HDD utilizing modern ML techniques and incorporating security mechanism for integrity of clinical data. The first contribution is to the construction of a framework for the Integrated Accurate-Secure Heart Disease Prediction (IAS)Model. The framework comprises of five modules for the prediction model.

i. Data Collection
ii. Pre-processing
iii. Feature Extraction
iv. Disease Prediction Process
v. Integrity Validation Mechanism (IVM)

The following is the structure of this paper. Section II discusses studies that are linked to the suggested methodology. Section III outlines the proposed approach briefly, while Section IV delves into the experiment's results and analyses. Section V contains conclusions and recommendations for future work.

2. Related Works

The authors of [15] presented a framework for observing people with heart failure based on IoT and computer-assisted diagnosis, using statistics from numerous sources. Initially, records from body sensors about heart disease indications was collected by mobile devices using Bluetooth sensors and delivered to a cloud DB using a smart gateway. Clinicians divided the patient-data into several classes based on their signs. In the end, the Internet of Things (IoT) and neutrosophic multi criteria decision making (NMCDM) techniques were used to detect, monitor, and manage cardiac defects with low expense and time spent evaluating the disease. The experimental results validated the advanced system's performance.

The authors of [16] proposed an automated diagnostic methodology for diagnosing cardiac disease. Normalization of feature vectors was performed first, followed by data partitioning into training and test datasets. Following that, using a statistical framework, collection and feature grading were performed on the processed data. The same subset of characteristics selected by the framework during the training phase was used for data evaluation. A neural network (NN) was utilized to train on sample data with a limited number of characteristics. Using the test data, the trained NN's performance was evaluated. The approach presented in [17] saved the values of basic health-related metrics using implanted sensors of the apparatus rather than smartphones or wearable-body sensors. For rapid and secure data transfer, this architecture made use of XML Web services. It may be perceived that the overall response time between the cloud data center and the local DB server keeps nearly stable as the raise in number of users.

The work [18] proposes a blockchain-based secure healthcare infrastructure. The block chain was used to ensure the transparency and control of document access, health history, and the shipment operations between two ends. The analysis of the model was based on illicit activities or communications by hostile IoT objects. The suggested system by the authors [19] consists of two sub-sections: the RFRS feature selection method and a classification model with an ensemble classifier.

The first process comprises of three stages:

(i) data discretization,

(ii) feature extraction using the Relief FS technique, and

(iii) feature reduction using the heuristic rough set reduction algorithm.

The model has been evaluated based on the input samples from Statlog (Heart) dataset available from the UCI database. Using a heart illness dataset, the researchers in [20] created a ML-based diagnosis method for heart disease prediction. They employed seven prominent ML algorithms, 3 attributes extraction models, the cross validation process, and seven model evaluation metrics for classifiers such result accuracy, specificity, sensitivity, Matthews' correlation coefficient, and processing time. The technology can effectively differentiate between the heart defects and healthy data.

A comparison study in [21] examined the capabilities of LR, SVM, KNN, ANN, NB, and RF algorithms to diagnose heart disease. The experimental results show that data pre-processing and element selection can ensure a higher accuracy of machine learning significantly. To ensure that the dataset was complete, most researchers substituted missing values during pre-processing by using the mean or the majority signal of that attribute. The missing valued occurrences were eliminated in various works [22] [23]. Due to the wide exploration space, image segmentation is a difficult task. It expands exponentially in proportion to the amount of characteristics in the dataset. During feature selection, an appropriate comprehensive search approach is necessary to tackle this problem. Furthermore, some research has used ensemble models to improve prediction accuracy by combining different basic learning methods. However, in terms of properly predicting disease, the efficacy of these approaches can be enhanced further.

DNN have recently been utilized extensively in detecting the heart defects based on the beat rate. Convolutional Neural Networks (CNN) has been utilized in certain research to grade PCG images in the temporal and frequency domains. For instance, the authors [25] classified heart sounds using 2 kinds of ML models such as SVM and CNN with spectrogram pictures

[24]. In [25], the authors investigated the value of utilizing CNN to classify normal and abnormal heart and lung sounds. They experimented with 1, 2, and 3 convolutional layers to improve classification accuracy. They got the greatest accuracy with two convolutional layers. In [26], the paper developed a CNN-based analysis approach for heart disorders. By identifying PCGs, this approach can determine whether a cardiac sound recording is regular or pathological. Adaptive Neural Fuzzy Inference System (ANFIS) and ANNs are also used in conjunction with various approaches to progress result accuracy. Using ANFIS, Bahekar et al. attempted to enhance the success rate of categorizing heart rate signals [27]. In another work, Eslamizadeh and Barati used ML algorithms to distinguish between normal and murmurous heart sounds [28]. Deperlioglu used ANNs with the resampled energy approach to improve classification accuracy over S1 and S2 sounds [29]. For observing the fourth cardiac sound (S4), authors in [30] used a Backward Time-Growing Neural Network (BTGNN) model. Cheng created a Laconic Heart Sound Neural Network (LHSNN) to execute a heart sound taxonomy result on low-cost hardware [31]. The authors emphasize, however, that detecting hidden biases in the dataset via machine learning techniques remains difficult.

3. Proposed Model

This section explain the complete working process of the proposed model, comprises of five phases, as follows.

i. Data Collection
ii. Pre-processing
iii. Feature Extraction
iv. Disease Prediction Process
v. Integrity Validation Mechanism (IVM)

Here, the classification is performed with Deep Convolutional Neural Networks (DCNN) based on the obtained input data. The system endures training and also evaluating to perform the classification. The cryptographic operations are used in the fifth phase for ensuring data security. The data came from two sources: the Internet of Medical Things (IoMT) and the UCI ML repository. Following pre-processing, the feature selection procedure is activated. Then the classification is applied to the specified data attributes. In the process of training, sensor data from a long-range (LoRa) cloud server is checked and rated as normal or defected. Furthermore, secure connection between components can be provided via a system security element, and the obtained statistics is safeguarded from hostile alteration and illegal admittance, boosting data confidentiality and system reliability. Figure 2 depicts the proposed framework.

A DCNN is used in the suggested method to forecast the patient's cardiac problems. The system is trained and tested for this purpose. The training results fall into two categories: (a) normal and (b) abnormal. Further, the testing phase is carried out. The medical-sensor gadget connected to the patient provides sensor rates indefinitely. The values are categorized with respect to training results, which denotes that IoT sensor data are compared to training phase values. The method evaluates the inputs and returns categorized results. The phases in the suggested model are detailed below.

3.1 Data Collection

Here, the data collection process is done in two ways, as mentioned before. The first way is to collect from the patients directly using medical sensor devices, such as, Respiration Rate (RR) Sensors, EMG, EEG and ECG devices, Oxygen Rate Sensors, which are described in detail below.

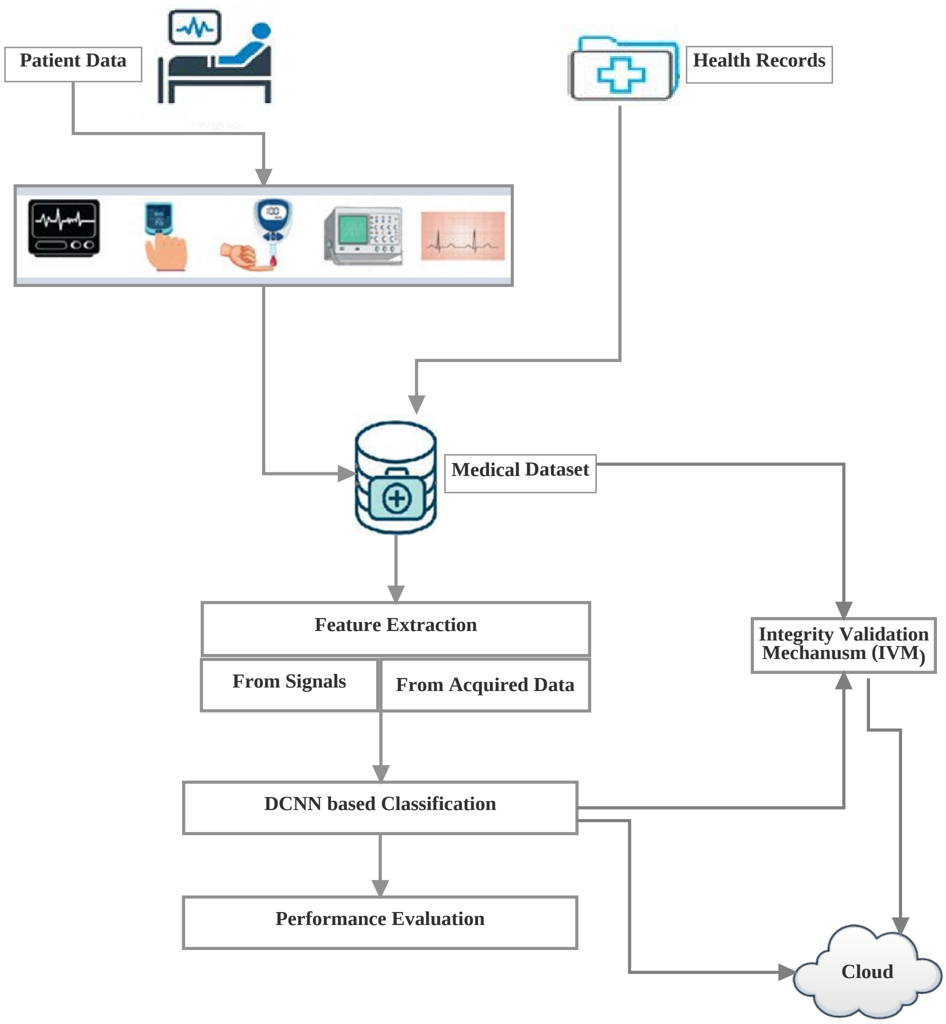

Fig. 2. Proposed Model Framework

A. RR Sensor

Sensor for respiratory rate: conventional pulse oximeters are utilized to measure respiratory rate. It determines flow rates per minute near the respiratory flow ‘0’ and identifies flow values of many hundred l/min. When defining Heart Rate Variability (HRV), the slow breathing mentioned as negative rate, with HRV segregations much lower when slow breathing was compared to quick breathing. As a result, assessing breathing rate is required for the diagnosis of cardiac disease.

B. EMG Sensor

An EMG sensor is a "mode for measuring and monitoring the electrical motion created by skeletal muscles" that is frequently used in bio-medical and therapeutic modules. The health of the muscles and nerves that govern them is estimated using EMG. "The EMG signal has a range of 0.1 to 0.5 mV" and is frequently measured in microvolt’s.

C. EEG Device

It measures the brain activity from the scalp. The cortical electrical activity is observed from the waveforms. It is used to determine neurological prediction in individuals who are unconscious following attacks, but its utility is restricted by differing descriptions of abnormal prototypes and inter-observer inconsistency.

D. ECG Device

ECG devices are used for observing the heart and pulse rate for defining the aberrant cardiac sounds and illness, which may cause heart failure.

E. Oxygen Rate Sensors

Oxygen rate in patient's blood is measured with the device called pulse oximeter. Furthermore, a drop in oxygen levels causes an increase in heart and pulse rate changeability, necessitating the measurement of oxygen levels to determine the current state of cardiac disorders. The acquired data and their respective units are given in **Table 1**.

Table 1. Units and Data Factors Collected from Sensors

Factors	Units
Respiration Rate	Breaths per minute (BPM)
EMG	Microvolts (mV)
ECG	mV
EEG	Milliseconds (ms)
Oxygen level	Percent (%)

The heart disease dataset [26] is used to train and evaluate the models. It consists of 1025 records, 13 attributes, and a single target line. The target column is divided into two classes, as 1 and 0: 1 denotes heart disease and 0 denotes non-heart disease. The specifications of the factors are described in **Table 2**.

Table 2. Heart-based Factors from Dataset

Factors	Description
Age	Patient's Age
Gender	1: male, 0: female
Chest Pain Types	1 typical angina 2 atypical angina 3 nonangina pain 4 asymptomatic
RestBP	Resting BP
FBS	Fasting blood sugar larger 120 mg/dl
Chol	Serum cholesterol in mg/dl
Exang	Exercise-induce angina
Oldpeak	ST depression induce: exercise relative to rest

The obtained datas are processed by the preprocessing and feature extraction, in which the data are denoted as,

$$Y_{pd}, d = \{1,2,\dots,m\} \quad (1)$$

Where the 'pd' is the patient data and the total number of obtained signals/data is 'm'.

3.2 Pre-Processing

Pre-processing is the initial process in this diagnosis process. It consists of three steps: attribute replacement, redundancy elimination, and separation. After reviewing the complete person's age group, cholesterol, and BP, the variable of a specific feature is substituted. The elimination of redundancy decreases data size by removing redundant (irrelevant) attributes.

3.3 Feature Extraction

3.3.1 Signal based Feature Extraction

The gathered signals Y are fed into the feature extraction algorithm, which calculates peak amplitude, total harmonic distortion, pulse rate, standard deviation and energy. It is effectively used for minimizing the duplicated data from the dataset inputs. It decreases computational complexity, boosts generality phases in the diagnosis model, and improves learning speed. The additional features are a condensed version of the previous set of features.

A. Maximum Amplitude

The highest positive/negative departure of a waveform from its '0' is defined as the peak amplitude of a sinusoidal waveform.

B. Total Harmonic Distortion (THD)

THD is defined as a amount of the harmonic distortion contained in a sign or computed as the rate of the power average of all harmonic factors to the frequency power elements.

$$\mathrm{THD} = \frac{\sqrt{\sum_{j=2}^{M/2} A_j^2}}{A_1} \qquad (2)$$

Here, the highest harmonic order is given as (M/2) and the j th amplitude of the harmonic rate is given as, 'A_j^2'

C. Heart Rate

When the cardiac rhythm is normal, the period between two successive QRS complexes (Q wave, R wave, and S wave, the "QRS complex") can be used to determine the heart rate. The heart rate is measured by dividing the large box amounts with the QRS complex.

D. Standard Deviation

It is measured to determine the number of average signal deviations. The variance rate of the power fluctuations are measured as in (3).

$$\sigma^2 = \frac{1}{M}\sum_{k=0}^{M-1}(x_k - \mu)^2 \qquad (3)$$

Here, the signals are represented in 'x_k' and the total samples are given in 'M' and the mean and standard deviation is given as, 'μ' and 'σ', respectively.

E. Energy

The energy of a signal is presented as 'X(u)', which is the primary of squared signal magnitude and is measured in (4).

$$\mathrm{Energy} = \int_{-\infty}^{+\infty} |y(u)|^2 du \qquad (4)$$

At last, the measured feature is presented as, $Tf_n, n = 1,2,\ldots,F$ and the whole amount of obtained features is given as, ‘F’.

3.3.2 Data based Feature Extraction

Some of the patient data is fed into the feature extraction phase, where the standard deviation, kurtosis, and skewness are employed for feature extraction. The obtained data 'X' is transmitted for reducing the needed resource numbers for derivations without avoiding vital columns. Hence, data duplications are also reduced, thereby, overfitting issues are also reduced.

A. Standard Deviation

The variance rate is measured based on the computations of deviations from the mean. Equation is used to calculate the standard deviation formula (3).

B. Kurtosis

This factor computes if the data is heavy-tailed or light-tailed in assessment to a normal distribution, as defined in (5).

$$\mathrm{K} = \frac{1}{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{D}}\left|\frac{(\mathrm{x_d}-\bar{\mathrm{X}})}{\sigma}\right|^2 \tag{5}$$

C. Skewness

It is defined as "a distortion or asymmetry in a set of data that deviate significantly from the harmonious bell curve, or normal distribution," as stated in (6).

$$\mathrm{SK} = \frac{1}{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{D}}\left|\frac{(\mathrm{x_d}-\bar{\mathrm{X}})}{\sigma}\right|^3 \tag{6}$$

The complete derived features from data are given as, $\mathrm{TF_{fs}}, \mathrm{fs} = 1,2,3,\dots,\mathrm{F_s}$, where the sum of data obtained is presented as ‘$\mathrm{F_s}$,’.

3.4. Classification using DCNN

The selected features are classified using the classification model. Each chosen feature is fed into the DCNN classifier as input. The weights are given arbitrary rates and are associated with each data. To obtain the result, random weight values increase the back propagation process, further, optimization is processed. These weights have a significantly influencing the classifier's output. The following are the analytical steps in the DCNN classification.

i. Let the selected feature rates and their corresponding weights be denoted using expressions (7) and (8):

$$Fet_i = \{Fet_1, Fet_2, Fet_3, \dots . Fet_n\} \tag{7}$$

$$wt_i = \{wt_1, wt_2, wt_3, \dots . wt_n\} \tag{8}$$

Where $\mathrm{Fet_i}$ denote the input rate, with ‘n’ number of features. And, $\mathrm{wt_i}$ denotes the weight rates.

ii. the arbitrarily chosen weight vectors are multiplied with the inputs and then add them up.

$$K = \sum_{i=1}^{n} Fet_i\, wt_i \tag{9}$$

Where, ‘M’ denotes the total rate.

iii. Determination of activation function

iv. Examine the output of the next hidden layer.

v. Each layer in the MDCNN is subjected to the three procedures outlined above. Finally,

assess the output unit by summing the weights of the inputs to determine the values of the output layer neurons.
vi. The network output is compared to the actual rate in this stage. The error signal is described as the variation between these two values.
vii. The output unit's value is compared to the goal value in this step. The associated error is identified.
viii. The back propagation model is used to correct the weights.

$$wt_i = \sigma\delta_i(Fet_i) \tag{10}$$

Where, 'σ' is the momentum and 'δ_i' is the distributed error rate. The proposed model has a higher predictive performance due to the decrease of mistakes. The approach then proceeded on to the testing step, which comprised using the dataset to train the model for detecting the diseases. Finally, the trained model is prepared to assess the input patient's statistics for heart disease detection, and the evaluate findings can be made accessible to the user and doctor.

3.5 Integrity Validation Mechanism (IVM) for Secure Processing

These databases, as previously stated, used as a chronological record for medical-based health data. The data information is stored on to the cloud. When a user accesses data saved in the cloud, it should be validated under IVM. Data consistency will be reviewed to ensure data integrity. The data owner must generate classification data for integrity testing before putting the data in the cloud. The data is generated by employing cryptographic hash methods and Message Digest routines. When a user has proper access control with appropriate access permission levels, can be allowed to perform the operations.Nonetheless, integrity checking is carried out to determine whether the received data has been altered by any unauthorized person. In that circumstance, the approach would include some jamming processes to terminate that specific user's access and prevent the owner's content from being outsourced in a modified form. The IVM procedure is used to prevent data tampering. In **Table 2**, the following algorithm outlines the working procedure of Hashing utilizing the algorithms SHA-1 and MD5, with the hypothesis that the block size is 64 bytes.According to the aforementioned conditions, the user's unauthorized access will be blocked when there is an timid activity is found, and the integrity of the medical data is checked for reliability and security.

Table 3. Algorithm for IVM in IAS

Function string hash_code (Key (*k*), Medical_data(*md*))
If len (*k*)>blck_S) then
Key=hash (*k*) // minimizes the key size
End if
If len (*k*)<blck_S then
Key= *k*‖[0×00* (blck_S -len (*k*))]
End if
OP_key_pad = [0×5c * blck_S]XOR key
IP_key_pad=[0×36*blck_S]XOR key
Return H(OP_key_pad‖hash(IP_key_pad‖md))
String 32 VALUE= MD5(HashCode(k, md))
End function

4. Results and Discussions

This section depicts the disease diagnosis model evaluation metrics. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) variables are used in the computations (FN). Below are the formulas for computing classification accuracy, precision rate, sensitivity, specificity, error rate, and F1-score.

$$ClassificationAccuracy = \frac{No.of correctly classified Samples}{No.of Samples processed} \times 100\% \quad (11)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (12)$$

$$Specificity = \frac{FP}{TN+FP} \quad (13)$$

$$ErrorRate = \frac{1}{k}\sum_{i=0}^{k}\frac{TN_k+FN_k}{TotalSamples} \quad (14)$$

$$Precision = \left(\frac{TP}{TP+TN}\right) \times 100\% \quad (15)$$

$$F_1 - Score = \frac{2*Precision*Recall}{Precision+Recall} \quad (16)$$

The findings are compared to those of established models like CNN, ANFIS, and ANN. The evaluations are processed using MATLAB. The results of the sensitivity and specificity rate study are depicted in **Fig. 3** and **Fig. 4**. When evaluated with a variety of datasets, both figures depict that the adduced model outperforms the comparative results on the basis of sensitivity and specificity. The use of feature extraction effectively helps the categorization process.

The classification accuracy and precision evaluations are also employed, with the results given in **Fig. 5** and **Fig. 6**. The proposed model achieves 96.3 % of the average, which is higher than other current disease diagnosis models, as per classification accuracy analysis. Furthermore, for model analysis methods, the average accuracy is taken into account, with the proposed model having a higher rate of precision. The training model was trained using the best attributes for disease detection using DCNN for classification.

DCNN is trained from instances in the proposed model for disease diagnosis. **Fig. 7** depicts the results of calculating the error rate. The error rates determined for the various datasets 10, 20, 30, 40, 50, and 60 are as follows: 17.1, 29.4, 35.9, 44.4, 36.2, 44.6, which is minimal than the other compared works and validates the efficacy of the proposed work. The proposed model used both signal and data based feature extraction, which helps DCNN to produce appropriate classification result, further aids in better decision making. When it comes to healthcare data processing, the most crucial factor is time efficiency in medicine to address patients immediately soon as feasible. As a consequence, time efficiency estimations are also computed, and the findings are depicted in **Fig. 8**. As illustrated by the graph, the model beats previous efforts in related to time effectiveness.

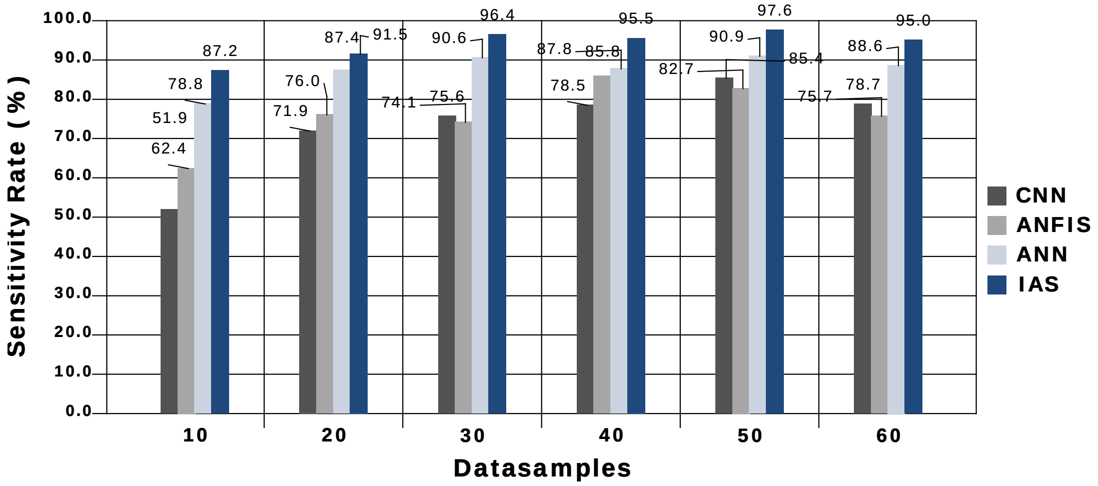

Fig. 3. Sensitivity Rate Vs Datasamples

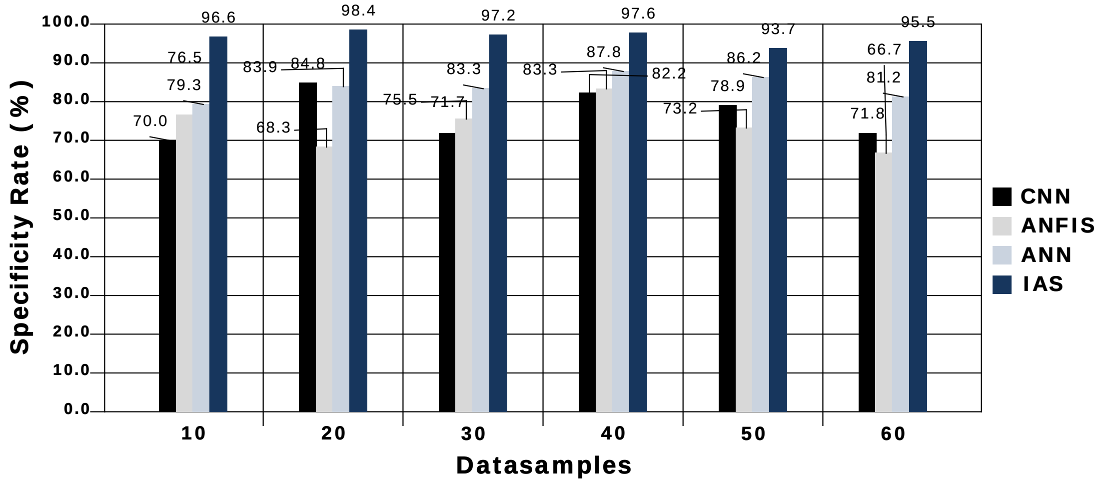

Fig. 4. Specificity Rate Vs Datasamples

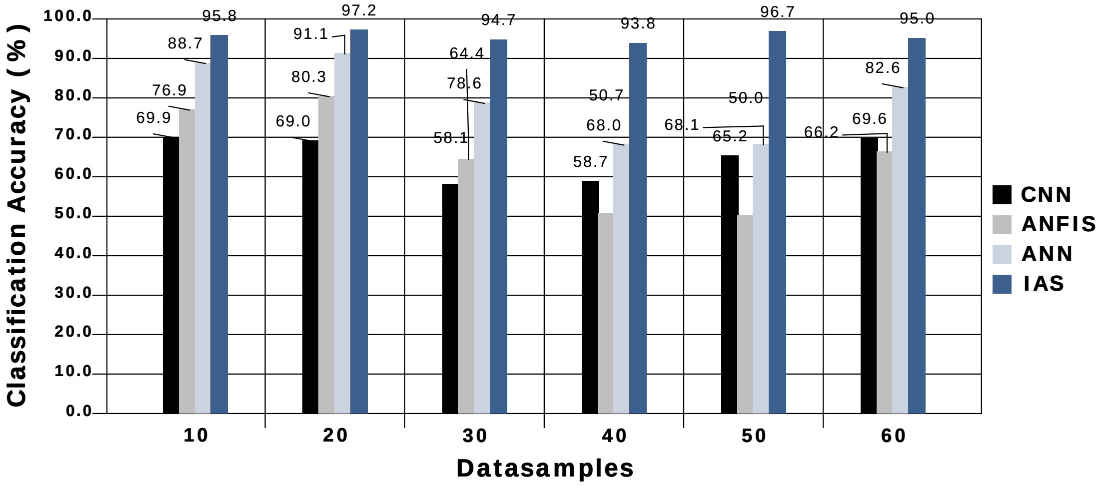

Fig. 5. Classification Accuracy Vs Datasamples

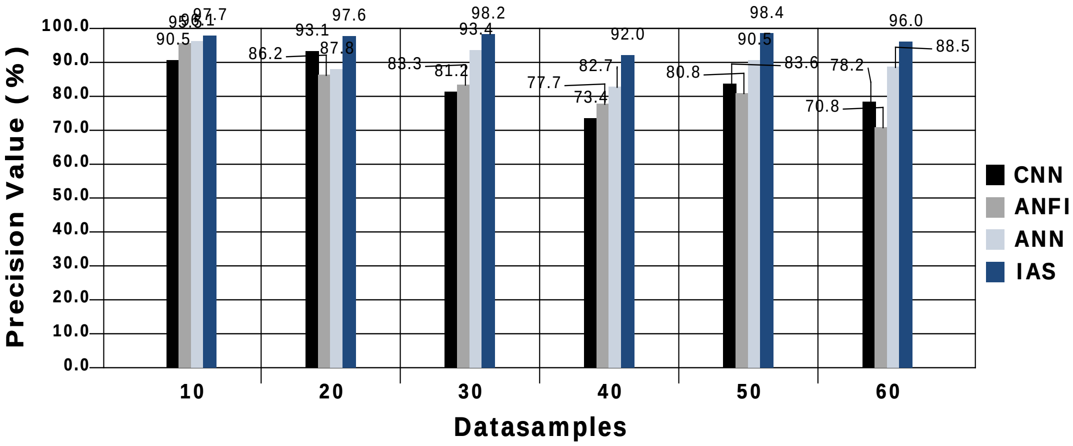

Fig. 6. Precision Value Vs Datasamples

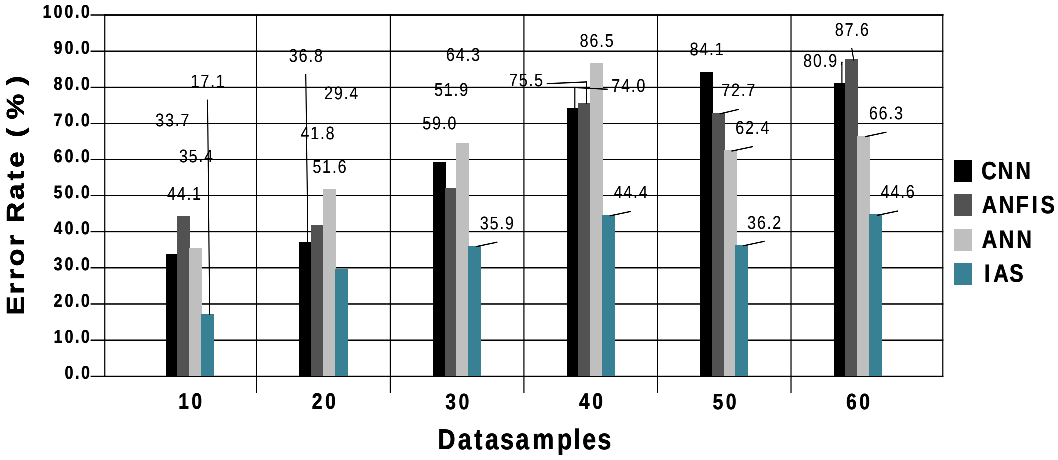

Fig. 7. Error Rate Vs Datasamples

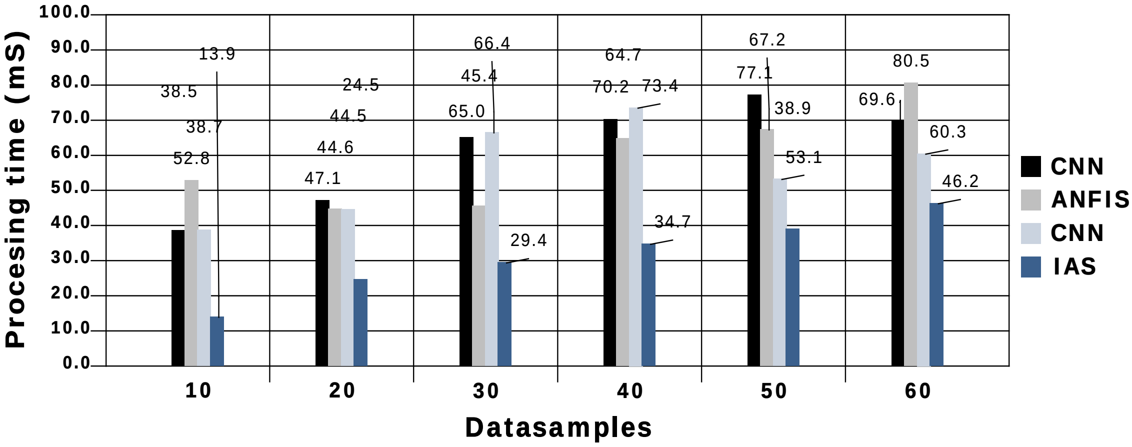

Fig. 8. Processing Vs Datasamples

5. Conclusions and Future Enhancement

With the use of Secure Cloud computing, this research sought to present a revolutionary smart healthcare paradigm. The proposed model gathered data from various IoMT devices. Here, the heart characteristic is extracted from both signals and data. The DCNN was used to provide all of these aspects to the diagnostic system. Furthermore, a hash-based integrity validation mechanism is used for security assurance of shared patient statistics over the cloud. The characteristics are analyzed, and then classification is performed to determine normal and abnormal heart activities using the DCNN. The performance of the proposed model is evaluated using the UCI dataset. The developed DCNN classifier also surpasses existing models in terms of accuracy. The results show that the proposed methodology outperforms the other alternatives in terms of accuracy. As a result, the smart health-care paradigm with IoT-based safe cloud computing has shown capable results.

To improve the predictive process performance in the heart disease diagnosis, the proposed model could be enhanced in the future by applying more complicated feature selection methods, computational efficiency, and classification methods. This paradigm can also be used in real-time applications.

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We, Syed Anwar Hussainy F and Senthil Kumar Thillaigovindan state that the content of this article entitled "An Integrated Accurate-Secure Heart Disease Prediction (IAS) Model using Cryptographic and Machine Learning Methods" does not contain any conflict of interest.

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