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# SMART DEVICES FOR MONITORING HEALTH AND DISEASES USING MACHINE LEARNING AND DEEP LEARNING METHODS

**Monelli Ayyavaraiah**
Assistant Professor
Department of CSE
Rajeev Gandhi Memorial College Of Engineering & Technology, Nandyal, AP, India

**Abstract:** Worldwide, heart disease is the number one killer. Prediction of heart disease is a very involved process. Early detection of cardiovascular disease signs is one of the most challenging challenges for doctors. Accurate medical choices may be made with the use of heart disease prediction data. Clinical decision-support systems have made extensive use of AI methods for illness prediction and diagnosis. Because of their potential to reveal previously unseen patterns and correlations in medical data given by medical practitioners, these methods are particularly beneficial for creating clinical support systems. A very accurate model is necessary to reduce death rates. Internet of Things (IoT), cloud computing, machine learning, and deep learning methods are employed to construct such precise models. Heart disease symptoms may be reduced and identified with the use of machine learning. The medical decision-making system is meant to aid doctors in their day-to-day work; hence it is an ever-present and regular activity. The accuracy of medical diagnoses is enhanced by the use of web-based healthcare systems. In order to foresee potential issues with clinical risk factors, doctors use a predictive modeling procedure. Early on, a number of different forms of learning technology are used to aid medical professionals in the identification of illness. An accurate, dependable, and continuous monitoring system is also required for prompt intervention and therapy. More strategies need to be developed for prediction models as illness prediction research continues to progress. Decision-making under uncertainty is handled by these models. The study's overarching goal is to develop better methods of early prediction and intervention for cardiovascular illnesses.

We designed a system that uses IoT to monitor patients remotely and accurately assess the degree of their cardiac condition as part of an automated e-healthcare monitoring system. IoT medical sensors capture data on a variety of patient clinical indicators, which are then used in classification algorithms to determine the severity of conditions including hypertension, hypercholesterolemia, and cardiovascular disease. In order to determine the precision with which cardiac illness may be predicted, researchers use machine learning and auto-encoder-based neural network algorithms. Using a total of 35 different clinical criteria, we develop a neutrosophic clinical decision-making system capable of scoring the severity of cardiac disease on a scale from 1 to 5. Furthermore, our suggested models are more accurate and efficient in predicting the existence of heart disease when compared to numerous previous studies.

**Keywords:** Heart Disease Prediction, Clinical Decision-Support Systems, Artificial Intelligence (AI) in Healthcare, Machine Learning, Internet of Things (IoT) in Healthcare, Remote Patient Monitoring, Auto-encoder-based Neural Networks, Clinical Risk Factors, Early Detection of Cardiovascular

Disease

## 1. Introduction

Computer science, Information science, and healthcare all converge in health informatics. It consists of several abilities, techniques, and devices to ensure the optimal. Flow of information, storage, processing, and use in health and biomedicine. Health informatics deals with the data mining process integrated with machine learning techniques for disease classification and prediction. Data mining techniques are used to discover hidden patterns in the healthcare industry for making disease prediction easier. In a remote patient monitoring system, the clinical data generates every second and processed simultaneously. With the numerous growths of patient data, there is a need for the latest algorithms and computational tools to categorize and handle the data. A significant amount of work has contributed to the integration of healthcare and smart device-based computing to form health informatics.

Due to rapid development in information technology excessive amounts of data are generated frequently in health care informatics, they are hospital information, patient information, disease information, and treatment costs [1]. These massive data are generated from a wide range of sources and formats and they may contain irrelevant features and missing data. DM employs a variety of techniques to extract knowledge from massive disease data sets. A DM algorithm identifies the hidden patterns in the dataset and transfers them into valuable information for making decisions. DM tools are used in healthcare to predict life-threatening diseases like cancer, diabetes, liver disease, and heart disease. To improve anticipating behavior and achieve better results, existing algorithms must be studied, analyzed, and rebuilt.

To analyze data and derive useful information, classification, clustering, and rule mining are used. The benefits of data mining are: forecasting future disease outcomes based on similar types of existing diseases, preprocessing noisy data, and minimizing disease diagnosis. Data mining can analyze disease symptoms efficiently due to its predictive power. It can able to organize the relationship between the user and decision management. Secondly, it has the capability for extracting the facility of decision making for disease diagnosis. Lastly, the noisy medical data will be pre-processed and include many attributes for decision-making.

Heart diseases become common in individuals in recent decades and it is difficult to find the presence of heart disease promptly and accurately by the healthcare providers [2]. Hence, it is important to use computer expertise for detecting the disease in the early phases with enhanced precision by healthcare practitioners. To preserve irreversible human lives, carly detection and treatment are essential. This research focuses on the early and accurate identification of cardiac disease. Several regression and classification techniques were examined in this study for effective prediction.

The following techniques are associated with Health care for disease prediction, (i) Machine Learning Techniques for Heart Disease Prediction (Regression and Classification) (ii) Ensemble Learning Techniques for Heart Disease Prediction (iii) Hybrid Optimization Techniques for Heart Disease Prediction (iv) Remote Health Monitoring for Heart disease Prediction (v) A Neutrosophic Clinical Decision-Making System for Heart Disease Prediction



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### 1.1 Machine Learning Techniques

In Disease Prediction Cardiovascular disease (CVD) becomes more prevalent in today's environment. Identifying significant features and behaviors of CVDs is much more difficult. Physicians can identify the presence of CVD by performing several diagnostic tests such as BP, ECG, blood sugar level, cholesterol tests, etc. These tests are typically expensive and time-consuming. Sometimes immediate medical attention is required when the disease becomes more severe. Due to the rapid increase in data, machine learning becomes an emerging field nowadays [3]. Machine learning assists in gaining insights from large amounts of data, which is an impossible task for a human. This research study also aims to identify some of the risk factors that contribute to CVD. Several machine learning algorithms are compared using various performance indicators through classification and regression techniques. Various ML algorithms are compared as per their prediction results.

Machine learning is a subset of Artificial Intelligence (AI). Machine learning became more popular today and expecting even more popular in the next few days. In this digital world through remote monitoring devices, massive amounts of data are collected by tracking the patients. Yearly 30% of global data are generated by the healthcare industry. It is expected 36% by 2025 [4]. Due to the huge amount of data, the traditional techniques failed to analyze this overloaded data. Building predictive models manually and analyzing the data is impossible in some scenarios. Even if it is time-consuming and less productive, Machine learning, on the other hand, provides reproducible outcomes and learns from previous computations. Supervised, Unsupervised, Semi-Supervised, and Reinforcement Learning are four main categories under machine learning. For labeled data supervised learning and unlabeled data unsupervised learning are used. Supervised learning techniques are used to solve a class problem. A machine learning model learns a mapping between the input and target variable [5]. A labeled training dataset is used to train the learning algorithms. These trained algorithms classify the unlabeled test dataset into similar groups. Supervised learning classified into Regression and Classification techniques. The relationships among the variables are determined through regression analysis. It can exhibit whether changes in one or more explanatory variables are related to changes in the dependent variable [6]. In the classification technique, the objects are classified by assigning each one through a set of classes. When an object is assigned exclusively to one class not more than one class is called 'Mutually exhaustive and exclusive' [7]. Each input is associated with explicit goal outputs and environmental evaluations in supervised learning, but in unsupervised learning the learner introduces existing prejudices about which features of the input's structure should be reflected in the output [8]. Classification algorithms are used to learn how to classify problem domain instances with a class label. Classification is an issue where an object is assigned to one among n classes based on the similarity measure of its features with each class. Classification can contain discrete input variables or real-valued. For example, it categorizes emails as "spam" or "not spam", a patient is "diabetic" or "non-diabetic", a patient's heart function is "normal" or "abnormal" etc. Regression techniques are used for model predictions where the projected output must be a continuous numerical value. For example, estimating a house cost depends on the size of the home, estimating a company's sales revenue depends on its prior sale information, etc. Calculating a person's risk of developing cardiovascular disease, the corresponding output variable has an actual value in regression issues.

## 2. Literature Review

Predicting heart illness using a few straightforward physical indicators through physical examination is a challenging job for physicians. Clinically, it is difficult to identify heart disease symptoms to make correct projections and make decisions for a future diagnosis. Analyzing a large volume of data manually is a time-consuming process. Online healthcare services can be provided using IoT and sensing technology. IoT devices are used in healthcare to generate huge amounts of information, and cloud computing approaches are employed to manage such data. Cloud and IoT-based healthcare applications are being created with the help of ML and DL algorithms to monitor and detect critical heart disease disorders and provide the user with high-quality service when using online healthcare services.

Al-Makhadmeh, Z., et al., [9] proposed an IoT-enabled medical device using BDBNN algorithms. The system's performance was calculated through loss function, ROC, specificity, and f-measure and achieved 99.03% of accuracy in the intricacy of 8.5s. Khan, M. A., et al., [10] developed a heart disease diagnosis and real-time health monitoring using an IoMT framework. In this paper, they investigated the key characteristics of CVD using modified M-SSA, an AN-FI system, and different ML techniques. The model achieved 99.45% accuracy.

Kaur, P., et al., [11] suggested an automated disease prediction model using MLP, KNN, DT, SVM, and RF. A heart disease dataset was collected that consisted of 297 instances. Out of 297 instances, 252 instances were selected from training and the rest 45 instances were selected for testing purposes. Using the WEKA tool the model was experimented for 303 patient samples belonging to 5 classes. The model produced 97.78% accuracy. Ahmed, F. et al. [12] proposed an IoT-based framework using an SVM algorithm. The model experiments evaluated cloud data using the WEKA framework and produced 97.53% accuracy. The suggested framework is accurately predicted on smaller datasets but for larger datasets, the performance is compromised. Pan, Y., et al., [13] suggested an Enhanced Deep Convolutional Neural Network (EDCNN) architecture using MLP and regularization learning techniques. The model evaluated on full set features and reduced features using Deep Neural Network (DNN), RNN, ANN, and EDL-SHS. The EDCNN model produced the highest precision value up to 99.10%.

Khan, M. A., et al., [14] presented an IoMT framework employing MSSO–ANFIS approach. The model was evaluated on a UCI repository heart disease dataset. For feature selection, the Crow search algorithm was utilized. Modified Salp Swarm OptimizationAdaptive Neuro-Fuzzy Inference (MSSO–ANFIS) approach obtained 99.45% accuracy and 96.54% precision. Ali, F., et al., [15] illness prediction model constructed utilizing ensemble DL and FF techniques. EMR and wearable sensors were employed to acquire the data. Information gain method used to clear the data. The model generated an accuracy of 98.50%. Jabeen, F., et al., [16] presented an IoT-recommended system utilizing NB, RF, SVM, and MLP. Using various biosensors the patient's data were obtained. The system generated 98% accuracy. Nashif, S., et al., [17] created a cloud-based cardiac disease prediction model employing RF, SVM, NB, and ANN algorithms. The data were acquired with a MOD-00158 heartbeat sensor. The model produced the highest accuracy for the SVM algorithm with



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97.53% as well 97.50% and 94.94% for sensitivity and specificity respectively.

Machine learning algorithms become more popular in the last decade, but their ability to address a wide range of issues has remained a mystery for years. The majority of these strategies are based on the assumption that data. If the learning issues are formally framed with ambiguous or inconsistent information, the ML will be unable to perform. The data need to be processed in the preparation phase, making the data science process exceedingly lengthy and impractical. SVNs are a structure for constructing faulty information. Single-valued neutrosophic algorithms deal with learning challenges including complicated information by manipulating imperfect data. Many ML techniques have recently been mapped into the NSs environment to increase the performance of existing learning algorithms and manage faulty input in the real world. The disease information is riddled with flaws, ambiguity, and imprecision, all of which might lead to an inaccurate diagnosis. To deal with vagueness and imprecision, Zadeh presented a novel notion called fuzzy sets in 1965 [18, 19]. Following that, various extensions of fuzzy sets were discovered, including NSs [20]. In 1999, Smarandache proposed neutrosophy as the discipline of philosophy. The neutrosophy is built up with the combination of NS and Neutrosophic logic. The SVNs are a variant of the NS [21]. Ye introduced [22] simpler neutrosophic sets

We reviewed the literature on medical diagnosis, neutrosophic sets, and medical diagnosis using NS, and recommender systems in this section. In the literature, various decision-making strategies have been presented, and some of them are discussed below. Ye, J. [21] proposed a unique SVNSM measuring method to handle multi-period medical diagnosis using tangent function. Using Pattern recognition instances, they compared their findings with similar kinds of problems. Then, using detailed information on a multi-period a multi-period medical diagnostic procedure was evaluated. Cui et al., [22] developed an extension termed A dynamic neutrosophic cubic set (DNCS) from neutrosophic sets. They used many periods to express the patient's symptom data. The disease symptoms were obtained at certain time intervals. Using DNCS the intervals were recorded. Different examples are used to test the usefulness of this technique.

Gulerial et al., [23] demonstrated a new parametric divergence measure for NS with numerous properties. The Parametric divergence was measured using classification and multi-criteria decision-making techniques, along with their implementation procedures. Additionally, numerical examples of application problems were used to demonstrate the proposed techniques. They also compared their findings to those of other researchers. Abdel-Basset et al., [24] designed a disease prediction model to identify smart medical devices and group decision-making. The model consists of neutrosophic bipolar consisting of priority techniques. The proposed study was performed on diabetes patients for identifying diabetes diagnostics and smart healthcare devices. The model was able to find the complexity of the problem and evaluate the smart healthcare devices under the supervision of medical diagnosis. The TOPSIS model was used to assess the neutrosophic results.

Ali, M., et al. [25] introduced a neutrosophic-based recommender system to diagnose the disease based on the values acquired from the algebraic neutrosophic measures. Here two criteria are considered, such as single-criterion and multi-criterion recommendation systems. Initially, the users are registered to the system, and the items are defined. Then, a utility function is specified to map the integers to the available ratings in the system. Further, the systems, features, and diseases of the patient are fed into the system. Next, indeterminate, truth, and false membership functions are mapped. The neutrosophic set components are thus formulated to diagnose the type of disease.

Table 1: An Automated Heart Disease Prediction Using IoT, Machine Learning, and Deep Learning Techniques

| S. No | Author | Model | Algorithm used | Results | Outcome |
|---|---|---|---|---|---|
| 1 | Ahmed, F. et al. [26] | An IoT-based Heart, Disease Prediction Framework | SVM | 97.53% | SVM |
| 2 | Samuel, O. W., et al., [27] | An Automated Heart Disease Prediction Model | Fuzzy_ AHP ANN | 91.10% | ANN |
| 3 | Reddy, G. T., et al., [28] | An Automated Heart Disease Prediction Model | BAT and RBFL | 78% | Rule-based Fuzzy Logic |
| 4 | Nashif, S., et al., [29] | A Cloud-Based CVD Prediction Model | NB, RF, SVM, and ANN | 97.53% | SVM |
| 5 | Al-Makhadmeh, Z., et al., [30] | An IoT-enabled Device For Heart Disease Prediction | BDBNN Algorithms | 99.03% | BDBNN |
| 6 | Kaur, P., et al., [31] | An Automated Heart Disease Prediction Model | SVM, DT, KNN, RF and MLP | 97.78% | SVM |
| 7 | Jabeen, F., et al., [32] | An IoT Recommended System | NB, MLP, RF, and SVM | 98.00% | SVM |
| 8 | Kwon, J. M., et al., [33] | An E-BM Prediction Model | Deep Learning | 91.20% | Deep Learning |
| 9 | Pan, Y., et al., [34] | An EDCNN Architecture | DNN, RNN, ANN, MLP, and Regularization Techniques | 99.10% | EDCNN |
| 10 | Khan, M. A., et al., [35] | An IoMT Framework | MSSO –ANFIS | 99.45% | MSSO – ANFIS |

## 3. Problem statement

The remote healthcare system has great promise for lowering the fatality rate and financial costs associated with HF. An effective system that performs intelligent data analysis is constantly in great



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demand. There are various tools for heart disease prediction. However, they are either expensive or inefficient. For data privacy and security the data can be encrypted before sending to the cloud. To prevent patient information from unauthorized accessing, the cloud data can be encrypted and after decryption, the data can be pre-processed [36]. Currently, the medical field is gathering data from various resources. By making the best use of this data, the physician can easily anticipate improved treatment solutions and enhance the complete delivery system in the healthcare sector. [37]. without a doctor's presence, a patient's health condition may result in an emergency. Because of the rise in health problems in today's world, personal health monitoring has become extremely important. To overcome such issues, an IoT based system is required for remote monitoring, prediction, and continuous diagnosis of cardiovascular illness.

An RHMIoT (Remote Health Monitoring IoT) framework is proposed in a secure IoT and cloud context using a lightweight block encryption and decryption approach. With IoT medical sensors, clinical data about the patient is gathered and used to classify the severity of hypertension, hypercholesterolemia, and heart disease. The accuracy levels of cardiac disease are calculated using DL and auto-encoder-based NN methods.

## 4. Proposed Methodology

Here, we will discuss the components of an RHMIoT framework, including the sensor layer, transport layer, and application layer. Data from a variety of Internet of Things (IoT) medical sensors is collected at the sensor layer. The Internet of Medical Things (IoMT) is a diagnostic system comprised of several sensors. Vital signs including blood pressure, heart rate, cholesterol levels, etc. are monitored by attaching various biological and wearable sensors to the patient's body. Figure 1 shows a flowchart of the suggested procedure.

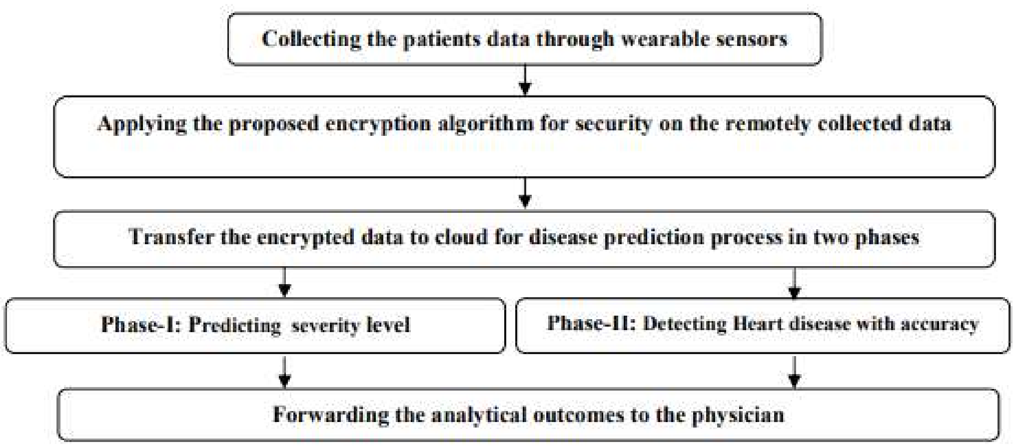


Figure 1: Flowchart of the proposed work

The doctors can monitor them from a distance. Using ML-based applications, physicians can continuously analyze their patients' diseases and health status using IoT medical sensors. This feature is one of the prominent features of remote health services. In our proposed RHMIoT system, patient data is gathered using a range of wearable sensors. For monitoring vital indicators of a patient various sensors are used in this study, such as a PPG sensor for Heart rate monitoring, an optical heart rate



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sensor for measuring the pulse waves, Sensitive Stretch Sensor for respiration rate, a Thermocouple sensor for measuring the body temperature, Pressure Sensor for monitoring blood pressure and pulse oximeter sensor monitoring blood oxygen level. The data is transferred to cloud storage using encryption and decryption techniques to prevent unauthorized users from accessing it. In the application layer, heart disease was predicted using ML and deep learning algorithms. Through the following steps, this section proposes a secure healthcare environment for heart disease prediction using a combination of several clinical parameters.

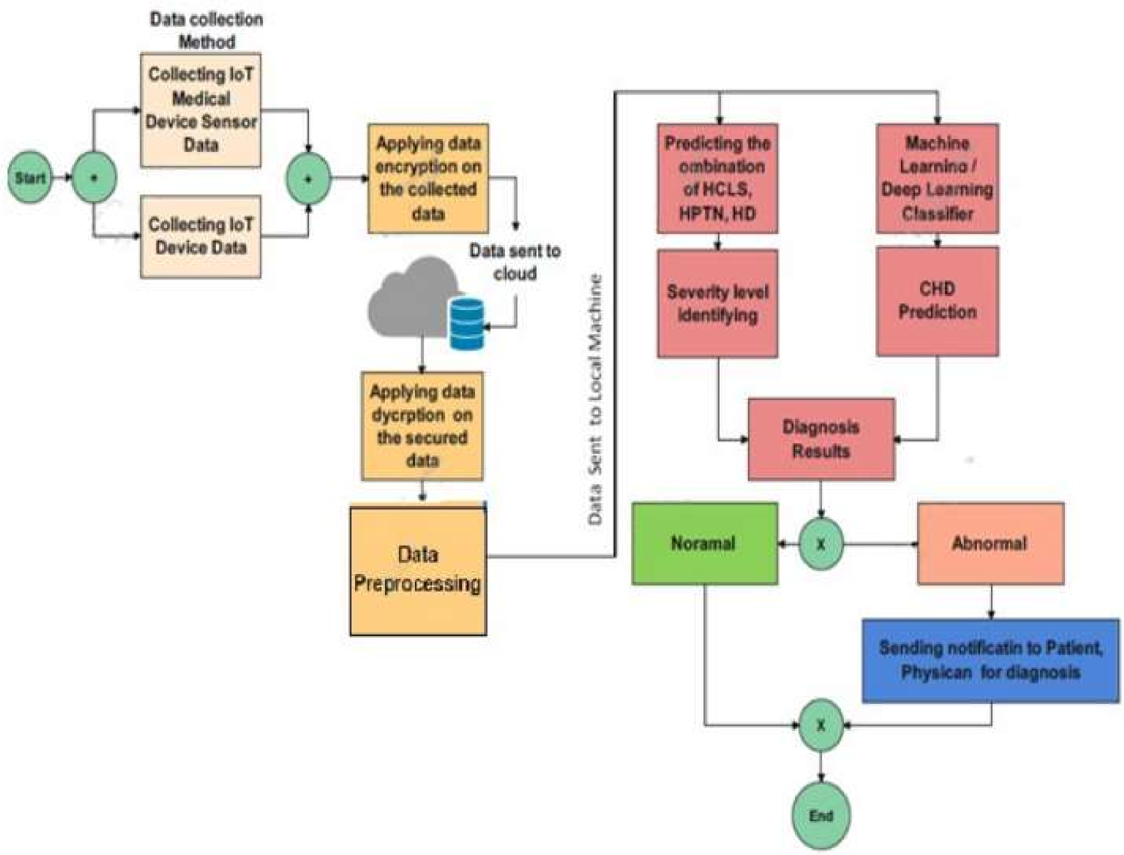


Figure 2: Workflow of RHMIoT Model

The model workflow is depicted in Figure 2. The flow of the model is represented through "+" and "x" symbols. The "+" symbol denotes the process with more than one procedure and the "x" denotes to process of only one. The collected data is encrypted using a block encryption technique and transferred to cloud storage for disease prediction. Finally, DL and Auto-encoder-based ML algorithms are applied for disease prediction. Patient information such as BP, blood cholesterol, heart rate, etc was collected using GPRS/LTE communication and ZigBee through Wi-Fi technologies.

**Algorithm 1 for collecting the IoT data for disease prediction**

Input: As input, we have examples of medical data gathered from sensors and Internet of Things devices.

Output: Precise diagnostic information Algorithm#1: Commence data collection procedure Input data from the Internet of Things device, including patient identifiers and clinical notes.



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Step 2: Collect sensor data from internet-connected medical equipment.
Step 3: Send the information to the algorithm to undergo a quick block encryption.
End

In IoT security is a significant challenge. A performance algorithm is used to encrypt sensitive patient data. A lightweight block encryption technique is proposed for confidentiality and security. The raw data is converted to chipper text to prevent unauthorized access. The algorithm-2 is used for encrypting the data at the cloud storage.

Algorithm 2 for Data Encryption service at the cloud storage
Input: Obtained the health records
Output: Encrypted information is the result.
2nd Algorithm: Data Encryption Begin first, examines what algorithm#1 has gathered.
Step 2: Use the lightweight block encryption technique of Algorithm #3 to encrypt the gathered medical data.
Step 3: Send the information to an encrypted, decentralized data storage system for medical records.
End

Encryption techniques have a limited impact on IoT security. S-Box is one of the strongest techniques for blocking ciphers. An algorithm designed for enhancing security with a key-dependent dynamic S-Box and a hyperelliptic curve. Algorithm-3 shows the S-Box algorithm for Security Enhancing.

**#Algorithm 3 for enhancing the security using S-Box Algorithm**
Input: Finite field Finite_n, Hyperelliptic curve HC over Finite_n, and the key λ
Output: Effective S-Box
**Algorithm#3: S-Box algorithm Begin**
Step1: Evaluate $\mathrm{DO}_{\alpha} = \sum_{\mathrm{n} \in \mathrm{c}} \mathrm{x}_{\mathrm{n}} \mathrm{N}$
Step2: Evaluate $\mathrm{DO}\beta = \lambda\mathrm{DO}\alpha$
Step3: Add R $= D_{\alpha} + D_{\beta} = \sum_{n \in c} x_n Q + \sum_{n \in c} y_n Q = \sum_{n \in c} (x_n + y_n) Q = (x_n + y_n)$
Step4: Remove n bits from$x_{\mathrm{n}} + y_{\mathrm{n}}$ to 16 words of $4 -$ bits
Step5: Calculate $x_{\mathrm{n}} \oplus y_{\mathrm{n}}$
End

The remotely collected medical data were encrypted to avoid cyber attacks such as malware, brute-force, and ransomware attacks. Encryption technique provides a secure environment on the computer networks and cloud. Encrypted medical data is decrypted from the cloud services for analysis and disease prediction. Algorithm-4 gives the data decryption service to the cloud storage algorithm. In the proposed RHMIoT model, the medical data were analyzed in 2 phases. The phase-I is for predicting Hypertension (HPTN) with its severity level and phase-II is for heart disease prediction using autoencoder-added ML and DL algorithms

#Algorithm 4 for Data Decryption service at the cloud storage
Input: Medical data is encrypted.



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Output: Medical information that has been tampered with the original data that the sender sent
Algorithm#4: Data Encryption algorithm Begin

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Step 1: First, decipher algorithm #3's obtained encrypted medical data.
Step 2: The second step is to unlock the information stored in the cloud.
Step 3: Upload the encrypted patient information to a cloud service for safekeeping and approval.
End

**4.1 Heart Disease Prediction**

The heart disease prediction accuracy is calculated in this phase using various DL and auto-encoder-based ML classifiers. Multiple medical signals are gathered to track the patient's heart health and determine the likelihood of heart disease. The model was educated using data collected from the Framingham Heart Study [56]. The dataset contains 16 attributes with 4238 instances. Out of 16 attributes we found some null values. Null values may build a biased ML model and it will produce incorrect results. Data pre-processing techniques are applied to the dataset to remove null values. Using the median studentized technique the residual is reduced. The missing values are updated with a median value of the attribute. After updating the missing and null values the dataset is normalized using the min-max normalization technique. Equation (6.1) shows the calculation for normalization:

$$\hat{V_{\mathrm{I}}} = \frac{\mathrm{V_I} - \mathrm{MIN_A}}{\mathrm{MAX_{A-}}\ \mathrm{MIN_A}}(\mathrm{NEW\_MAX_A} - \mathrm{NEW\_MIN_A})\mathrm{NEW\_MIN_A}$$

In the above equation, the min (A) returns the min value, and max (A) returns the max value of the attribute. After pre-processing the dataset feature selection and classification techniques were applied. The patient's heart condition was determined using a training and testing dataset with an 80:20% ratio.

Dataset1 Source: https://www.kaggle.com/datasets/aasheesh200/framingham-heartstudy-dataset

**4.2 Deep Learning Algorithms**

Deep Learning (DL) is the subset of machine learning. A DL algorithm is trained with known historical data. The DL models are divided into training and prediction. The features and labels from historical data are extracted to predict outcomes during the training stage. The model is tested using MLP, CNN, and PNN algorithms for heart disease prediction.

**4.3 Multilayer Perceptron (MLP)**

MLP is a feed-forward ANN that is used to generate outputs from a group of inputs. Feed-forward NN is used among a group of connections for artificial neurons using an input, hidden, and output layer. This method makes it possible to group items into probabilistic predictions. The MLP helps to build real-time non-linear model learning. The output and hidden layer results are calculated through the following equation:

$$\mathrm{GET(A)} \ = 0(\mathrm{C(2)} + \mathrm{B(2)H(A)})$$
$$\mathrm{HIDDEN\ (A)} = \Phi(\mathrm{A}) = \mathrm{S(C(1)} + \mathrm{B(1)A)}$$

The required parameters for learning the model are defined in equation:

SET $\theta$ = { B(1), C(1), B(2), C(2)}

For calculating the value of s the tanh function is shown below:

$$\tanh(a) = \frac{e^3 - e^{-3}}{e^3 - e^{-3}}$$

**4.4 Convolution Neural Network (CNN)**

CNN w has the ability of feature learning. Hence CNN is a suitable algorithm for heart disease prediction at an earlier stage. We can use CNN for binary classification [23]. In Heart disease prediction a patient suffering from CHD is classified as "1" and not-subfreezing classified as "0", which is called a binary classification. CNN architecture operates in a single-input and single-output sequential mode. The CNN architecture relies heavily on the convolution layer for feature extraction. Linear and nonlinear processes include convolution and activation functions. The equations (6.5) show the convolution procedure for CNN:

$$y_i^{l+1}, j^{l+1}, d = \sum_{i=0}^{H} \sum_{j=0}^{W} \sum_{d^1=0}^{D^1} f_{i,j,d,d}^{l} \times x_{i^{1+1+i,j}}^{l+1+j,d^1}$$

**4.5 Probabilistic Neural Network (PNN)**

PNN algorithm maps input patterns over several classification levels. It follows the Bayesian decision rule. PNNs are a subclass of RBF networks that is more helpful for nonlinear mapping, class membership probability estimation, and likelihood ratio estimation. Compared to other algorithms PNN is faster in the training process. The PNN can be expressed in the following equation:

$$y_g(x;\sigma) = \frac{1}{\lg\,(2\pi)^{\frac{n}{2}}\sigma^n} \sum_{i=1}^{l} \exp\left(-\sum_{j=1}^{n} \frac{\left(x_{ij}^{(g)} - x_j\right)^2}{2\sigma^2}\right)$$

**4.6 Auto Encoder Added Machine Learning Classifier**

It has the capability of finding patterns and structures for unlabeled data. Denoising, adversarial, complete, and sparse autoencoders are variations of autoencoder techniques. For dimensionality reduction, the autoencoder trains the network to ignore irrelevant input while learning. Autoencoder contains an encoder and decoder. To reduce the higher-dimensional space to lower-dimensional space encoder is used, where a decoder converts the lower-dimensional space to higher-dimensional space. Numerically, the given input 'X' is called the encoder, and X' is called the decoder. To minimize the dimensionality autoencoder uses non-linear optimization techniques. Equation below shows the hidden layer calculation process:

$$H = \sigma(W \times X + b)$$
$$X = (W \times X + b)$$

Kernel SVM (K-SVM) A kernel function in SVM is used for classification problems. The kernel function allows the conversion to a linear decision surface when the data points are nonlinear. It calculates the product of two inner points. K-SVM defines the notation of similarity, for a high-dimensional space with little computational cost. In addition to kernels, SVMs use regularization to reduce the overfitting issues. The rules of kernel function and polynomial kernel rules are defined in the following equation.

Kernel (m') = 1 0 if|| m'|| ≤ 1 otherwise



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PK $(m_x, n_y) = (m_x, n_y + 1)d$

**4.7 Weighted KNN (W-KNN)**

It is one of the variations of KNN. The weights are assigned to the nearest k locations. W-KNN gives more priority to the points that are closer and gives less priority to the points that are in distance. The hyperparameter k influences the performance of the KNN algorithm. When the value of k is low then the algorithm becomes more sensitive towards the outliers. Even KNN finds difficulty in combining the class labels. The weighted KNN classification algorithm is a simple technique to predict a class that has two or more numeric predictor variables. The inverse distance function for a weighted KNN is calculated through equation:

$$y' = \arg\max_{v} \sum_{(x_i, y_i) \in D_z} w_i \times I(v = y_i)$$

**4.8 Bernoulli Naive Bayes (BNB)**

It is part of NB. It implements a Bernoulli distribution technique for binary classification. When the features of the dataset are binary then the BNN algorithm can be used. The probability of a task is calculated through the Bayes theorem. In NB an equal weight is given to all features and each feature is treated independently. BNB produces more accurate results with faster computation. The Bernoulli distribution is calculated in equation:

$$b(X1) = B[X1 = x1] = \begin{cases} Q = 1 - bx = 0 \\ bx = 1 \end{cases}$$

The BNB classifier rules are defined through equation:

P1(M||N)P = (i|N) × Xi + (1 − p(i|n))(1 − xi)

## 5. Result And Discussion

An RHMIoT mechanism using DL and autoencoder-based machine learning classifiers is proposed in this section. The model was evaluated on the Framingham dataset. The dataset is further classified into 80:20 ratios. The performance is calculated through Accuracy, Recall, Precision, F1- Score, and F1 –Beta Score. The F1-beta score is calculated in the same way as the F1 score. In contrast to F1 Score, which is the harmonic mean, it is the weighted harmonic mean of precision and recall, with a best value of 1 and a worst value of 0. The weight of recall in the combined score is determined by the beta parameter. Equation shows the F-Score and F1- Beta score formula

$$\mathrm{F1-Score} = 2 \times \frac{\text{Precision X Recall}}{\text{Precision X Recall}}$$

$$\text{F1} - \text{Beta Score} = F_b = \frac{(1+\beta^2) + \text{PrecisionXRecall}}{(\beta^2\ \text{XPrecion}) + \text{Recall}}$$

In the proposed RHMIoT model six different classification algorithms were used in phase-II. The performance of each experiment is compared through performance metrics and statistical results. Table 2 shows the performance metrics. Figure 3 depicts the performances of the proposed algorithm. K-SVM and BNB achieved the highest accuracy with 0.87% and F1-Score is achieved for MLP and CNN with 0.54%. For early diagnosis of heart disease, more attention is given to-wards achieving maximum true positives.



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**Table 2 Summary of Performance Metrics**

| S. No | Name of the algorithm | Accuracy | Recall | Precision | F1-Score | F1-Beta Score |
|---|---|---|---|---|---|---|
| 1 | MLP | 85.00% | 54.00% | 65.00% | 54.00% | 57.00% |
| 2 | CNN | 85.00% | 54.00% | 66.00% | 54.00% | 57.00% |
| 3 | PNN | 85.00% | 50.00% | 42.00% | 46.00% | 44.00% |
| 4 | Kernel SVM | 87.00% | 50.00% | 44.00% | 47.00% | 45.00% |
| 5 | Weighted KNN | 85.00% | 51.00% | 53.00% | 50.00% | 51.00% |
| 6 | BNB | 87.00% | 50.00% | 69.00% | 47.00% | 47.00% |

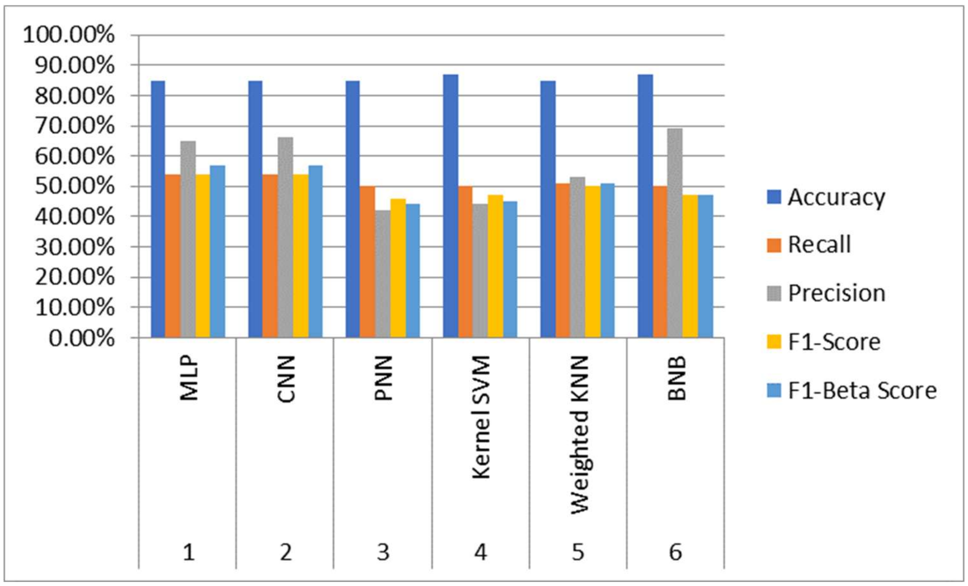


Figure 3: performance metrics comparison

## 6. Conclusion

The worldwide use of remote health monitoring has increased in recent years in response to the epidemic of CVDs. This method is useful for diagnosing patients in rural areas or at home. For a safe RHMIoT, we provide here a lightweight block encryption and decryption method. The proposed model is put through its paces in two stages, using data gathered from a wide array of IoT medical sensors. In this first stage, we will use data mining methods to determine the severity of HCL, HPTN, and HD. In Phase II, we'll use a number of Deep Learning and Autoencoder-based machine learning algorithms to make predictions about heart disease. Multiple performance matrices were used to arrive at the final results. The auto-encoder Kernel SVM model has the highest performance accuracy (87.00%) when compared to other machine learning and Deep Learning methods.

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