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# IoT-Cloud-based Smart Healthcare Monitoring System based on Seahorse Optimization-driven Mutated CNN

***Abstract:*** - Healthcare is undergoing a transformation due to predictive analytics, which offers clinical decision support in real-time, facilitating effective, tailored therapy. By lowering unfavorable events and raising the standard of care, this approach supports patients at every step of diagnosis, prognosis and therapy. Predictive algorithms driven by artificial intelligence (AI), machine learning (ML) and Internet-of-Things (IoT) handle enormous amounts of data, with cardiovascular illnesses as the primary cause of death worldwide. IoT devices make sophisticated deep learning (DL) analytics and remote patient monitoring possible. This paper presents a novel 5-stage disease prediction model as an IoT-cloud-based smart healthcare management framework, constructed using a seahorse optimization-driven mutated convolutional neural network (SHO-MuCNN). In stage-1, data is gathered from a variety of sources through data collection. The stage-2 of data pre-processing involves the use of standardization to get the data acceptable for additional processing. Using a customized principal component analysis (CPCA), the set of characteristics is determined in stage-3. Next, the stage-4 diseases are predicted by the suggested SHO-MuCNN methodology. According to the prediction results, physicians are educating patients in stage-5 on exactly what measures can be taken to reduce the risk. The smart healthcare monitoring measures for accuracy (98.56%), precision (96.69%), F1-score (97.86%), Recall (94.59%)and AUC (95.02), were employed in the models' performance. In addition, this study utilizes the SPSS and t-test for statistical analysis. The experiment's findings indicate that the SHO-MuCNN strategy outperformed the remaining techniques in an intelligent healthcare monitoring system.

***Keywords:*** Monitoring, Prediction, Cloud, Deep Learning (DL), Smart Healthcare, Internet-of-Things (IoT), Seahorse Optimization-Driven Mutated Convolutional Neural Network (SHO-Mucnn), Heart Disease Risks

## 1. Introduction

Predicting heart disease automatically is one of the biggest and trickiest real-world health concerns. Heart disease damages a patient's body, especially in elderly people and it is linked to coronary artery infections, which also affect blood vessel function. According to the World Health Organization (WHO), heart-related conditions account for the majority of deaths globally [1]. The way society functions are completely transformed by the rise of IoT. It creates a wealth of chances to raise one's standard of living in every sector, from banking to industry to education, from higher productivity in business to automation and control [2]. The IoT is constantly changing and has an influence on many aspects of our lives, much like a living thing. The IoT connects information, people, things/objects and processes, ranging from robots in factories to domestic appliances. Cloud computing (CC) provides practically infinite processing and storage capacity while providing elastic on-demand services [3]. A change towards patient-centered care is signaled by the rise of telemedicine, which allows for better patient-provider contact and ongoing monitoring. The emergence of health monitoring technology is facilitated by this change, increasing the effectiveness and accessibility of patient health management [4]. There are several techniques for taking a person's body temperature and heart rate both invasively and noninvasively. Over time, noninvasive methods have shown to be accurate and practical for the consumer [5]. The IoT cloud-based smart healthcare management system presented in this study is an innovative disease prediction model built with a SHO-MuCNN.

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The following sections comprise the remaining portion of this report: section 2 contains the related works. Section 3 describes the procedure. Section 4 deals with the experimental results as well as discussion and section 5 present the conclusion and suggestions for more research.

## 2. Related Works

The paper [6] suggested a smart home health monitoring system that assists in analyzing the patient's blood pressure and glucose data while they were at home and alerts the healthcare practitioner to any abnormalities found. The paper [7] used seven ML classification algorithms to forecast nine deadly illnesses, including thyroid, diabetes, hepatitis, liver disordersand heart disease, dermatology and breast cancer.The paper [8] suggested method used the Cascaded Long Short Term Memory (CSO-CLSTM) illness diagnosis model, which was based on the CSO algorithm. The paper [9] used sensing devices to gather data from the patient's body at first. Following transmission via a gateway and WiFi, the information was stored in a cloud repository for the Internet of Medical Things (IoMT). The paper [10] introduced a new class of adversarial techniques intended to exploit ML classifiers employed in smart health systems (SHS). They consider an adversary with partial knowledge of an SHS model, spreading information and ML algorithm for both focused and untargeted attacks. The paper [11] developed a sustainable lung cancer diagnosis model with the least amount of environmental impact by integrating artificial intelligence (AI) with the IoMT. The devices continually maintain communication and produce patient data. The paper [12] suggested a fog computing approach to reduce latency in healthcare together with cloud computing and IoT sensors. To intelligently separate patient information and reduce latency utilizing fog computing, employ a random forest (RF) ML technique. The paper [13] presented a Deep Learning-based Optimization (DLO) and SHM System for Agricultural Machines using IoT and AI. To optimize the process of monitoring the health of agricultural machinery (AM), this research proposed the use of artificial neural networks (ANN) and Fusion Genetic Algorithms (FGA). The paper [14] proposed the Intelligent IoT Framework for Personalized Healthcare (IIFPH). Real-time patient tracking and diagnosis are facilitated by ML techniques. The paper [15] employed a decentralized computational phenomenon employing hybrid computing architecture and suggested a wearable smart system for early detection of heart attacks, taking into account the sensitivity of this situation. The paper [16] suggested the design of a heart disease-focused Smart Healthcare Surveillance System (SHSS) and examined and evaluated the performance of several ML algorithms for the prediction of cardiac disease. The paper [17] used fog and cloud computing technologies to evaluate health big data from within the IoMT architecture and wireless body area networks (WBANs). The paper [18] recommended the Grey Wolf and Hybrid Whale Optimization Technique (Hyb-WGWO), the cluster head was selected in this case. To the cluster head, data from the cloud server were delivered.

## 3. Proposed method

An essential acquisition component for numerous real-time applications that promote communication among people and substance are IoT. The healthcare organization has a great deal of challenges in processing, storing and managing the vast amounts of data created by IoT devices. The data collection, data pre-processing, customized principal component analysis (CPCA) and disease prediction utilizing a seahorse optimization-driven mutated convolutional neural network (SHO-MuCNN), as shown in Figure 1, are among the components of the suggested smart healthcare system for predicting the risk of heart disease.

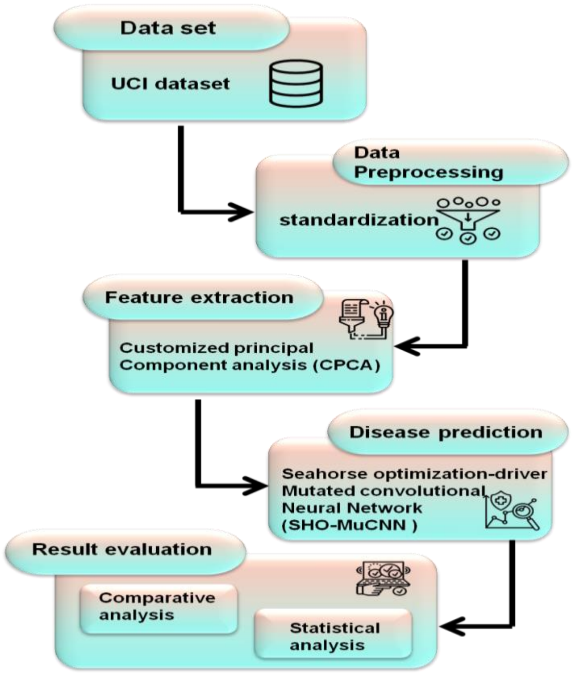


**Figure 1: Flow chart for the proposed method**

### 3.1 Dataset

The University of California, Irvine (UCI) dataset for the ML repository contains the Heart Failure Clinical Records Dataset. The medical records of individuals with heart issues comprise the dataset (https://archive.ics.uci.edu/dataset/45/heart+disease). This database has 76 features, however only 14 of them are used in the research that has been published. In particular, ML researchers have used one database so far, the Cleveland database. The goal field displays the heart status of the patient. Its integer value ranges from 0 (no existence) to 4. The goal of every experiment conducted with the Cleveland database has been to distinguish among present (values 1, 2, 3, 4) and absent (value 0). The dataset's detailed information is shown in Table 1.

**Table 1: Dataset description**

| Attributes | Type | Demographic | Description | Units | Missing value |
|---|---|---|---|---|---|
| Gender | Group | Gender | - | - | no |
| Age | Number | Age | - | Yrs | no |
| trestbps | Number | - | blood pressure at rest (at the time of hospital admission) | Mm Hg | no |
| chol | Number | - | serum cholestoral | mg/dl | no |
| cp | Group | - | - | - | no |
| restecg | Group | - | - | - | no |
| exang | Group | - | Angina brought on by exercise | - | no |
| oldpeak | Number | - | Exercise-induced ST depression in comparison to rest | - | no |
| thalach | Number | - | Maximum heart rate achieved | - | no |
| fbs | Group | - | fasting blood sugar > 120 mg/dl | - | no |

### 3.2 Data preprocessing using standardization

Data normalization entails squaring risk variables and allocating values that illustrate departures from the mean standard deviation. With a standard deviation $(\sigma)$ of 1 and a mean $(\mu)$ of 0, it rescales the risk factor value to enhance the performance of ML classifiers. Standardization's mathematical form is provided by (1).

$$Standardization\ of\ Y = \frac{Y - Mean\ of\ Y}{Standard\ deviation\ of\ Y} \quad (1)$$

### 3.3 Feature extraction using customized principal component analysis (CPCA)

The linear feature extraction technique CPCA is frequently employed to decrease linear dimensionality. To optimize the severability of categories for dimensionality reduction, it finds a new feature by using the variance of each feature. To make the modified variables uncorrelated, its basic principle is to eliminate closely related variables and add as few new ones as feasible. During this time, the converted variables should accurately reflect the data.

$$x = ({\xi_1}^S(y-y), \xi 2T(y-y), \dots, \xi dT(y-y)) \in \mathbb{R}^d \quad (2)$$

The average of a training set and a covariance matrix is determined given a training set $Y = y_1, y_2, \dots, yN(y_i \in \mathbb{R}^D, i = 1,2,\dots,N)$ and a lower dimension. The eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_D$ and related eigenvectors $(\xi_1, \xi_2, \dots, \xi_D)$ are obtained by performing a spectral decomposition on the covariance matrix. Equation (2) expresses any $y \in \mathbb{R}^D$ new low-dimensional representation.

### 3.4 Classification using seahorse optimization-driven mutated convolutional neural network (SHO-MuCNN)

The seahorse optimization-driven mutated convolutional neural network (SHO-MuCNN) is the method used to choose the ML algorithms to utilize. The algorithms were selected as possibly superior alternatives to the algorithms employed in the present experiments. The models were utilized to forecast the risk of heart disease.

#### 3.4.1 Seahorse optimization (SHO)

The migratory, breeding and feeding habits of the sea horse serve as models for the sea horse. Seahorses move about and look for food in a communal manner, which serves as inspiration for the SHO algorithm. The following is accomplished by applying the exploration and exploitation meta-heuristic. The breeding process enters its final stage as the two components disappear. This provides a thorough explanation of the SHO process, as following equations (3), (4) and (5).

$$T = \begin{pmatrix} w_1^1 & \vdots & w_1^C \\ \vdots & \ddots & \vdots \\ w_0^1 & \cdots & w_o^C \end{pmatrix} \quad (3)$$

$$W_j = [w_j^1, \dots, w_j^C] \quad (4)$$

$$w_j^i = rand\ \times (VA^j - KA^i) + KA^i \quad (5)$$

Where $T$ represents the variable dimension and $w_o^C$ the population's size. Upper and lower limits are the probabilistic results of any solution, denoted by $VA$ and $KA$. In the interval$[0,1]$, a random number is represented by a rand. When it comes to physical fitness,$w_j^i$ is the emblem for those that match the requirements for elite rank. By swimming, hunting and procreating, $SHO$ emulates the actions of seahorses.

**a. Seahorse movement behavior**

One might interpret seahorse behavior in terms of the normal distribution. The two case studies show the ideal line separating exploitation and exploration.

**Case 1:** The agent spirals towards the Xelite and continually modifies the rotation angle to expand the area of the locally-solvable problem space. The following are the mathematical Equations (6), (7) and (8) for the first scenario;

$$w_{new}^{1}(s+1) = W_j(s) + Levy(\lambda)\left(W_{best}(s) - W_j(s)\right) * w * z * y + W_{best}(s)) \quad (6)$$

$$Levy(y) = T * \frac{\omega * \sigma}{|l|^{\frac{1}{\lambda}}} \quad (7)$$

$$\sigma = \left(\frac{\Gamma(1+\lambda) * \sin\left(\frac{\pi\lambda}{2}\right)}{\Gamma\left(\frac{1+\lambda}{2}\right) * \lambda * 2^{\left(\frac{\lambda-1}{2}\right)}}\right) \quad (8)$$

Where the logarithmic spiral that establishes the length of the rod is defined by the constants$u$ $(default = 0.05)$ $andv$ $(default = 0.05)$, by $\sigma.y$ as an arbitrary total,the statistics $k$ and $w$isarbitrary[0,1]. The fixed infinite of 0.01 is $s$.

**Case 2:** A seahorse becomes a seahorse by moving in a Brownian motion in reaction to ocean waves, which increases its traversal. This should be stated correctly as following equations (9) and (10):

$$w_{new}^{1}(s+1) = W_j(s) + rand * k\ \beta_s * \left(W_j(s) - \beta_s * w_{best}\right) \quad (9)$$

$$w_{new}^{1}(s+1) = \begin{cases} W_j(s) + Levy(\lambda)(\left(W_{best}(s) - W_j(s) * w * z * y + W_{best}(s)\right), q_1 > 0 \\ W_j(s) + rand * k * \beta_s * (W_j(s) - \beta_s * W_{best}(s) q_1 < 0 \end{cases} \quad (10)$$

Where $\beta_s$ is the random walk coefficient for Brownian motion, while 1's value never changes, $q_1$is represented as an accidental value.

**b. Seahorse foraging behavior**

Seahorses are limited to two possible outcomes when they look for food: success or failure. With A, the condition is met. At this point, the seahorse outpaces its target in speed. When the response is higher than expected, though, it denotes a failure condition. Seahorses meet the following success and failure criteria when searching for food, following Equation (11):

$$w_{new}^{2}(s+1) = \begin{cases} \alpha * \left(W_{best}(s) - rand * w_{new}^{1}(s)\right) + 1(1-\alpha) * W_{best} \quad , if q_2 \geq 0.1 \\ (1-\alpha) * (w_{new}^{1}(s) - rand * W_{best}) + \alpha * w_{new}^{1}(s), \ if q_2 \leq 0.1 \end{cases} \quad (11)$$

Here $w_{new}^{1}$ is the seahorse's unique location. $q_2$is the coincidental sum of $[0, 1]$.

**c. Seahorse breeding behavior**

During the mating season, the male and female populations of seahorses are equally distributed.

$$\begin{cases} Fathers = W_{sort}^{2}\left(1: \frac{o}{2}\right) \\ Mothers = W_{sort}^{2}\left(\frac{o}{2} + 1: o\right) \end{cases} \quad (12)$$

Sorted $W_{sort}^{2}$ values provide Equation (12) the result in descending order of severity. The selection of $Fathers$ and $Mothers$ was arbitrary. Every pair harvests one child in the SHO operation.

### 3.4.2 Mutated convolutional neural network (MuCNN)

The MuCNN is commonly employed as a model for the DL technique in data processing and expression applications due to its excellent feature extraction and recognition performance. It is also of great relevance to the industrial sector. MuCNN has numerous layers as a neural network (NN). The shared weights of MuCNN are used to simplify and modify the neural network's structure. A convolutional network is composed of Fully Connected Layer (FCL) etc. The Conv-pooling module is used to extract features in a consecutive order.

**Convolutional Layer (CL):** A CL, also known as a feature extraction layer, it's an N layer used to extract features and mitigate the impact of noise. By applying a series of convolution kernels (CK) to the input data, CL generates the processed feature map. Every CK in a CL receives data from kernels in the layer below it in a local region. It is a local receptive field associated with distinct geographic regions. Through the establishment of local receptive fields, CKs can extract numerous properties. The way a CL works is described by Equation (13),

$$a_v^u = \varphi\left(\sum_o a_o^{u-1} * j_v^u + c_v^u\right) \tag{13}$$

The feature map obtained from the $v^{th}$ filter in the $j^{th}$ layer is denoted by $a_v^u$ in this context. $a_o^{u-1}$Explains the nth map of the $u-1$ layer mentioned,∗represents the convolution process. $j_v^u$is the CK of the $v^{\text{th}}$filter in the $u^{th}$layer. $c_v^u$denotes" bias φ (.). This value denotes the activation function, such as Rectified Linear Units (ReLU).

**Pooling layer (PL):** PL is also known as feature mapping layers and sample layers. Its major purpose is to extract secondary attributes. The pooling operation's goal is to shrink the network by down-sampling the convolutional feature map. Max pooling is a prominent pooling technique.

$$D_v^u = \max_{(s-1)Y<s<qY}\{a_v^{u-1}(s)\}\; q = 1,2,\ldots \tag{14}$$

Where Y is the pooling window size, q is the number of steps moved, $a_v^{u-1}(s)$ (s) represent the value of the $s^{th}$neuron in the $v^{th}$filter" of the $u-1^{\text{th}}$ layer and $D_v^u$ is the feature map obtained from the nth filter of the $l^{th}$layer.

**Fully connected layer (FCL):** The results of the previous PL are transferred into the FCL for further processing of the features. The FCL's primary function is to connect results to the soft-max classifier and extract additional features. The FCL is composed of several different levels. The operation of an FCL is described by Equation (15),

$$gr^{u+1} = \delta\left(F_{gr}^u gr^u + c_{gr}^u\right) \tag{15}$$

Where $F_{gr}^u$is the connection weight matrix,$c_{gr}^u$ is a bias, $\delta(.)$ is the activation function, and$gr^u$is the output of the $j^{\text{th}}$ layer. The cross-entropy function is then used to compute a loss function. The cross-entropy function, which is a valuable "error metric function for pattern recognition," is described in Equation (16).

$$Q(F,c) = -\frac{1}{C}\sum_{y=1}^{C}[I^y 1x(e) + (1-I^Y)\, 1x(1-e)] \tag{16}$$

Where $a$ total number of samples, $I^Y$ is the $Y^{th}$sample's actual value, and f is the classifier's "soft-max classifier."

The SHO-MuCNN integrates seahorse optimization with mutant convolutional neural networks (CNN), is used in the healthcare monitoring system powered by IoT and Cloud. This method improves network design performance for better healthcare data analysis. The system facilitates rapid interventions and individualized treatment by monitoring patient health parameters in real-time through the use of IoT devices and cloud infrastructure.

## 4. Result and discussion

In this paper, we employ our project using Python, a laptop running Windows 10 with an Intel i3 CPU and 32 GB of RAM. The SHO-MuCNN algorithm is compared to the existing approaches, including XGBoost [19], Support vector machine (SVM) [19] and adaptive Light gradient boosting machine (LightGBM) [19]. The parameters include Accuracy, Precision, F-score, Recall and AUC. Table 2 shows the outcomes of the proposed and existing methods.

**Table 2: Outcomes of the proposed and existing methods**

| Methods | Accuracy (%) | Precision (%) | F-score (%) | Recall (%) | AUC |
|---|---|---|---|---|---|
| XGBoost [19] | 86.88 | 89.65 | **87.50** | **84.84** | **87.07** |
| SVM [19] | 88.52 | 88.23 | 89.55 | 89.55 | 88.31 |
| LightGBM [19] | 91.80 | 92.41 | 92.06 | 92.06 | 92.15 |
| SHO-MuCNN [Proposed] | 98.56 | 96.69 | 97.86 | 94.59 | 95.02 |

Accuracy is defined as that a measurement reflects the real, recognized value. The term accuracy describes the degree of agreement between measurements taken of the same object. The fundamental metric is accuracy, which is calculated by dividing the total number of forecasts by the number of forecasts that are accurate. Precision indicates how closely two and more measures are related to one another by describing the amount of information a number can transmit in terms of its digits. The classifier's capacity to compute normal data in the absence of constraints is its definition. Figure 2 shows a comparative examination of accuracy and precision for both proposed and existing methods. The proposed SHO-MuCNN method provides accuracy with 98.56% and precision with 96.69%, respectively.

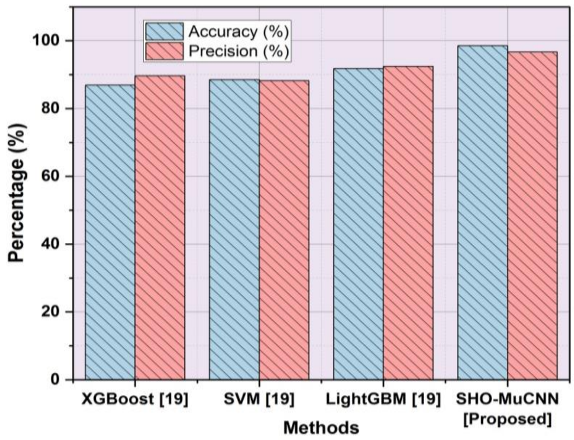


**Figure 2: Comparison of the accuracy and precision**

To calculate a harmonic average of the recall and accuracy of the suggested model, one component is created by combining both into the f1-score. The recall is to determine the percentage of true positives that were successfully identified. The percentage of actually significant instances in a collection of data, are other names for recall, which quantifies how well a model finds all relevant observations. Dividing the total amount of positive findings by the entire number of appropriate instances provides the total in one method. A comparison of the suggested SHO-MuCNN framework's F-score and recall with existing schemes is presented visually in Figure 3. The SHO-MuCNN provides F-score (97.86%), and recall for the proposed method (94.59%), respectively.

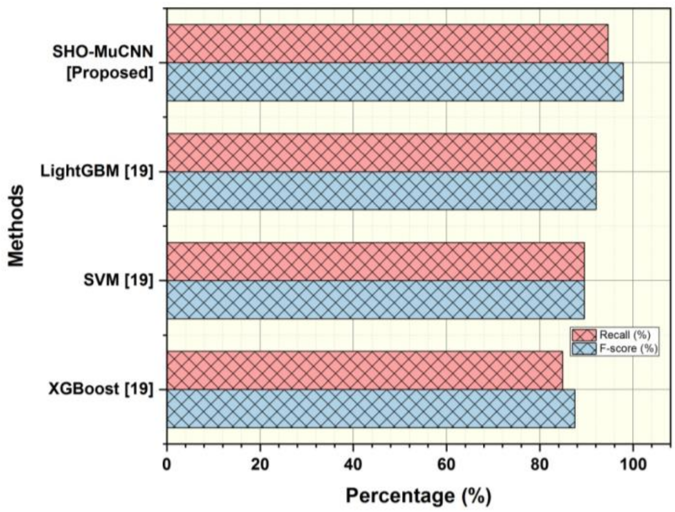


**Figure 3: Comparison of the F-score and recall**

The most effective method SHO-MuCNN for assessing the effectiveness of biometric systems is the AUC. Plotting the data makes it evident, that the suggested approach for human verification is unquestionably superior to the multi-biometric features. Figure 4 depicts the outcomes of the AUC for both suggested and existing techniques. The F-measure of SHO-MuCNN is determined and outputs are contrasted with existing methods including linear SVM (88.31), XGBoost (87.07), LightGBM has (92.15) and SHO-MuCNN has (95.02) in terms of AUC. The proposed SHO-MuCNN method performs better than other methods.

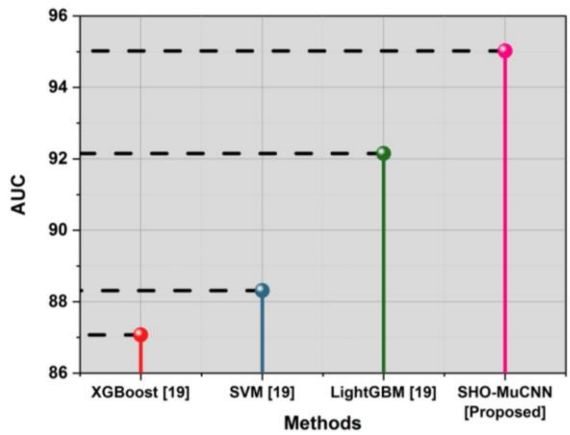


**Figure 4: Comparison of the AUC**

### 4.1 Statistical analysis

For statistical analysis in this study we utilize the SPSS tool. To determine if there is a significant difference between the means of each group and their connection, an inferential statistic known as a t-test is employed. Table 3 shows the analysis of standard deviation, mean accuracy, and loss. The standard deviation slightly changes, suggesting that SHO-MuCNN, a new classifier, is more dependable for achieving superior outcomes.

**Table 3: Descriptive Statistics for Loss and Accuracy**

| Parameters | Methods | Standard Deviation | Mean | Standard Error Mean |
|---|---|---|---|---|
| Accuracy | XGBoost [19] | 1.265 | 86.88 | 0.259 |
| | SVM [19] | 1.875 | 88.52 | 0.315 |
| | LightGBM [19] | 2.152 | 91.80 | 0.298 |
| | **SHO-MuCNN [Proposed]** | **0.546** | **98.56** | **0.218** |
| Loss | XGBoost [19] | 2.257 | 4.25 | 0.569 |
| | SVM [19] | 4.963 | 5.24 | 0.654 |
| | LightGBM [19] | 3.524 | 4.69 | 0.596 |
| | **SHO-MuCNN [Proposed]** | **1.254** | **3.52** | **0.485** |

The significance error is smaller than the recommended method and the significant value is less than 0.05, an independent sample t-test is performed for the SHO-MuCNN classifiers using the SPSS tool, as shown in Table 4.

**Table 4: Outcomes of T-test**

| Metrics | | Equality of variances | | Means Equality (T-test) | | | | | 95% difference in confidence interval (CI) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Sig | F | $df$ | $t$ | Std. error | $p$-value | Mean diff | Upper | Lower |
| Accuracy | Equal variance not assumed | - | - | 15.712 | -19.351 | 0.55 | 0.000 | -10.080 | -9.830 | -12.354 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Equal variance assumed** | .140 | 3.487 | 19 | -19.351 | 0.55 | 0.000 | -10.080 | -9.830 | -12.384 |
| **Loss** | **Equal variance not assumed** | - | - | 15.845 | 19.562 | .553 | 0.042 | 10.150 | 12.475 | 8.015 |
| | **Equal variance assumed** | .165 | 3.212 | 19 | 19.562 | .553 | 0.041 | 10.150 | 12.442 | 8.024 |

## 5. Conclusion

The study suggested the method for an IoT-Cloud using a smart healthcare monitoring system is utilized as a SHO-MuCNN. The suggested approach outperforms previous innovative heart disease prediction models accuracy (98.56%), precision (96.69%), F1-score (97.86%), Recall (94.59%) and AUC (95.02) with a significant value of less than0.05. The DL models have a great deal of untapped potential in healthcare research; this is only one aspect of the field's use of predictive analytics. A customized diet and exercise plan based on an individual's health status and the advice of a heart specialist can be automatically generated by improving the model. The proposed smart heart disease prediction system gathers data from IoT devices, with the cloud handling other important duties. The investigation showed that the suggested system performs admirably when compared to conventional approaches. Further research into DL models for the suggested smart framework is the goal going forward. When fog and edge computing are used, accurate and timely sickness predictions coupled with prompt responses and adaptable medical decision-making have altered the efficacy of the healthcare sector and enhanced the whole IoT.

**Author Contribution format:**

Conceptualization: Preetha P; Methodology: Preetha P; Formal Analysis and Investigation: Preetha P, Dr.A.Packialatha; Writing-Original draft preparation: Preetha P; Writing-review, and editing: Preetha P; Resources: Preetha P, Dr.A.Paclialatha; Supervision: Dr.A.Packialatha.

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The datasets created during development and analyzed during this work was found in the below mentioned repository: https://archive.ics.uci.edu/dataset/45/heart+disease

**Conflict of Interest:**

The authors declare no conflict of interest.

**Ethical approval:**

Any of the authors investigation with human Participants or animals are not included in this work.

**Informed Concerned:**

Any of the authors investigation with human Participants or animals are not included in this work.

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