ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

ENHANCED SALP SWARM OPTIMIZATION WITH ARTIFICIAL NEURAL NETWORK TRAINING FOR HEART MONITORING IN IOMT CLOUD ARCHITECTURE

M. Lorate Shiny[1,2], Kalpana Murugan[3*], Nagaraj Ramrao[4]
[1]Research Scholar, Department of Electronics and Communication Engineering, Kalasalingam Academy of Research and Education, Krishnankoil,Virudhunagar,Tamilnadu, India-626126.
[2]Assistant Professor, Department of Electronics and Communication Engineering, Dayananda Sagar University, Bangalore- 560068.
[3*]Department of Electronics and Communication Engineering,Kalasalingam Academy of Research and Education, Krishnankoil,Virudhunagar,Tamilnadu,India-626126.
[4]Vice Chancellor,Mohan Babu University, Tirupati, Andhra Pradesh, India-517102.
maxlinshiny@gmail.com[1,2], drmkalpanaece@gmail.com[3]*, nagaraj.ramrao@gmail.com[4]

ABSTRACT
The use of Internet of Medical Things (IoMT) in human-healthcare systems has enabled the gathering of sensor data for the diagnosis and prognosis of cardiac disease. However, handling big data, including clinical, omics, and health data, in actual- time can be challenging due to issues such as noise, size, formats, missing values, and a large number of features. This can make it difficult for health monitoring systems to gather accurate data. To address these challenges, an consideration based Convolution Neural Network methodology (ACNN) and an Enhanced Salp Swarm Optimization established Extended Short-Term Memory technique (Enhanced SSO-LSTM) model have been proposed. This approach consists of four layers: the actual-data gathering level, cloud data - storage layer, data analytics layer, and display layer. The primary sources of data handled by the data gathering layer include wearable sensor devices, medical records, the heart dataset, and the diabetes dataset. The cloud storage layer uses a wireless network to store all the data that has been gathered from the cloud server and various datasets. In the data analytics layer, large data analytics operations such as pre-processing, dimensionality reduction, filtering, and classification are carried out. A Health care expert can evaluate the patient's condition using the Enhanced SSO-LSTM classification findings in the display layer. The Enhanced SSO-LSTM model achieved accuracy in the range 96% with accuracy 93%, recollection of 85%, and F-measure in 80% of ranges. The ACNN model had 93% accuracy, 89% precision, 89% recall, and 79% F-measure. Overall, the Enhanced SSO- LSTM model demonstrated improved performance in large dataset health monitoring.
Keywords: Heart monitoring, wearable sensor devices, IoMT, salp swarm optimization

1. INTRODUCTION
Smart healthcare offers platforms for connecting resources, people, and organizations while facilitating the easy entry of health documents via devices like wearable appliance, the IoT, and the mobile Internet. Numerous stakeholders are involved in providing smart healthcare, including doctors, nurses, hospitals, and research institutions. The artificial based intelligence (AI), Internet depending Technology like IoT, big data, the Internet, 5G and cloud networking are examples of automated networks that are used in smart healthcare, along with cutting-edge biotechnology.
Cardiovascular disease is a leading cause of death worldwide, with an estimated 18 million deaths in 2015 according to the World Health Organization [1]. If left unchecked, symptoms and syndromes can become dangerous and even fatal. One in five people are at risk of developing heart disease over their lifetime. Despite various approaches used in the healthcare industry, predicting heart disease can be difficult due to the presence of both relevant and irrelevant factors in health data. It is important to be able to identify and focus on the important factors in order to make timely and accurate predictions.
Heart disease prognosis has been achieved using a variety of conventional clustering techniques [2]– [12].

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

Heart disease detection using conventional clustering methods frequently results in delayed and incorrect diagnoses. They experience significant computational costs, long convergence times, additional parameters, local optimum stagnation, and stagnation.

IoMT is a network of software and medical hardware. IoM [13] offers the service for gathering patient data and transferring it to healthcare professionals. IoMT has changed how patients and doctors interact, making it simpler to give patients personalized care while also encouraging preventative health. The healthcare sector has adopted the IoMT in order to increase the effectiveness of the sector by deploying IoT-connected equipment. Technology is being used by businesses and hospitals to track down patients and remotely monitor them. IoMT is frequently employed in patient monitoring applications through connected devices.

Over the past few years, medical institutions have undergone tremendous change because of technological advancement. But medical services are scarcer for residents of remote locations. E-health services are an effective way to lower the danger of heart disease, mortality, and the cost of clinical tests [14], [15]. Health tracking also makes use of sensors that track movement, heart rate of a patient, and blood pressure of a patient.

The following is the contribution of the enhanced SSO-LSTM methodology:

- Clustering methodology based on Fuzzy (FC) is often will be defined for the minimization of data- size based on its data set qualities.
- To determine the best hyperparameters, the upgraded SSO is used with the LSTM. The LSTM approach correctly identifies patients' psychological state (stress, depressed, happy, and normal), blood pressure (low BP, high BP and normal BP), diabetes (low diabetes, high diabetes and normal diabetes), and BP.The improved SSO increases both exploitation and exploration possibilities by including an inertia weight parameter.
- Additionally, a cardiac monitoring system is identified by analyzing clinical data and an attention-based convolutional neural network (ACNN).

The following is how the remaining sections are arranged: The enhanced SSO-LSTM and attention-based CNN approach are described in Section 3 along with a brief explanation of their advantages and disadvantages. Section 4 presents the investigational arrangement and evaluation study, and with future research directions defined in last section(section 5).

2. LITERATURE SURVEY

[18] describes the development of a large big data system that depends on the dual-directional lengthy-small-term memory based (DMBi-LSTM) technology and DM. For the reduction in healthcare data count, heterogeneous information was first pre-processed using the DM technique. Next, ontologies will be implemented to give a semantic acquaintance of blood pressure and high glucose level. The third point is that Bi-LSTM is utilised towards anticipate patients' nonstandard circumstances then bad medicine reactions. One constraint is the incapacity of text data forecasting to analyze and enhance the work is to define LSTM supported fuzzy technique to get better healthcare classification performance.

[8]suggested employing stacked lengthy-small-term memory which stands on behalf of SLSTM to predict blood sugar levels. It is mainly developed for preprocessing and prediction. Kalman smoothing was employed in the preprocessing stage to fix CGM (Continuous Glucose Management) reading issues. Next, they used SLSTM to forecast blood sugar levels. Although this approach has few reading errors, it is not very accurate [9] Enhanced SVM-kernel technology was added to the healthcare monitoring system to forecast diseases. In the data preprocessing stage, the noisy and undesired data are initially removed. The crucial traits were then determined using the chi-square approach. The SVM-kernel tricks finally forecast illnesses. High precision was provided by this method, although the time commitment is greater.

This method uses a lot of resources [16] and proposed neural networks and fuzzy systems for health

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

monitoring systems. The system's effectiveness is increased by using the fuzzy technique [17]. To predict diseases, EDLMs, or ensemble deep learning methods, were added to the healthcare monitoring system. After gathering electronic medical records and sensor data, the technique of feature fusion is used to combine the key features. Utilizing the information gain method, the redundant and unnecessary features are then removed to reduce the computational load and enhance system performance. Finally, the disease prediction approach uses deep learning. The system complexity is reduced using this technique, but the unnecessary features are not eliminated [18]. Later, introduced the BiLSTM Neural Network in the healthcare monitoring system. This technique improves the predictability of psychiatric illnesses in people.

Reshma et al. [19] established as a three-stage method on the basis of artificial neural networks for HD expectation on angina. Through the methodology, we can able to attain an data-accuracy rate of 88.89%. Samuel et al. established a refined medical decision support system for HD diagnosis. The system combines a neural network with a fuzzy analytical hierarchy approach. The proposed methodology shows data-accuracy as 91.10%.

An IoT-based system for diagnosing cardiac illness that makes use of a deep belief neural network model was reported by Al-Makhadmeh and Tolba [20]. Any unaccounted-for values were checked against the collected data. The researchers investigated the data distribution. The authors used the studentized technique to normalise the data. Deep belief networks and a high-order Boltzmann machine were used to extract features from noise-free data. The authors' 99.03 accuracy rate contributes to a reduction in heart disease mortality.

Vivekanandan et.al., created a comprehensive model that includes a feed forward neural network, a fuzzy analytical hierarchical methodology, and a modified differential evolution (DE) technique [21]. Feed Forward neural network a modified differential evolution methodology was used to choose the most important traits. To predict heart illness, a having a features given to an optimized results for a fuzzy based AHP with help of Feed Forward neural network. The reported simulation outcomes are depends on the revised evolution technique, which would be 83% correct. Using a genetic approach based on recurrent fuzzy networks, Uyar and Lhan [22] examined heart illness. The proposed heart disease monitoring algorithm was evaluated using UCI dataset. Patient information was collected by using a data processing system, and an additional study was developed using a fuzzy technique.

A cardiac disease prediction algorithm was created by Ahmed et al. [23] using an Internet based technique framework. In some recommended work, support vector machine plays a major role. The cloud uses WEKA framework. Through SVM, the datas are analysed in the expectation of the cardio illness. The researchers claimed that their technique had 97.53 accuracies in predicting heart disease. Their system gathered heart-related data, including human-blood pressure, human-body hotness, and heartbeat, using an IoT device. This method has proved successful in accurately diagnosing cardiac disease. The proposed approach identified heart illness quickly, but correctness suffered as soon as a large quantity of data is employed.

Table 1. Survey of the existing work

Authors	IoT Device	Methodology	Accuracy
[20]	Yes	higher degree Boltzmann, full with belief neural network	95.03%
[21]	No	With fuzzy AHP-FFNN, modified E	83%
[22]	No	RFNN trained by GA	95.78%
[23]	Yes	KNN	96%
Proposed	Yes	Enhanced Salp swarm optimization with LSTM	96%
	Yes	ACNN	93%

3. PROPOSED METHODOLOGY

The IoT and cloud computing has become increasingly important in providing services for a variety of

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

applications as Internet services have developed in the recent years. In order to overcome cloud difficulties including the inability to meet requirements and constrained scalability, centralized IoT-based computing systems are needed. The vast amounts of data were utilized in the proposed work for developing the potential-sensitive frameworks such as investigation schemes and fitness observing.

In order to create a real-time healthcare monitoring system, the research proposes an IoMT-based cloud environment with ML algorithms. The intended work is broken down into four phases. IoMT medical sensors will be implemented in the initial stage towards collection of factual-stage data on patients. Utilizing the data that has been collected and uploaded to a cloud server, the second phase comprises data computation. Next stage, the biomedical data will be used aimed at ML classification algorithms and the data's are stored and accessed from the cloud server. Giving the patient or doctors access to the managed data. The data's will have storage space using cloud methodology on a cloud server and enables instant therapy, is the fourth phase.

The Internet of Medical Things (IoMT) is a special field of IoT technology in the health sector. Figure 1 depicts the application, network, and perception levels, generally known as the classic three-step strategy for an application based on IoT. IoMT focuses mainly on perception layer, which consists of two sublayers: access to data layer and acquisition system layer.

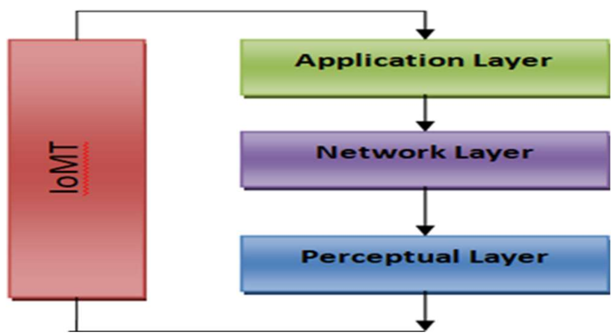

Figure 1: Internet of Medical Things architecture

The network layer is further classified into service layer and networking transmission sublayers. The subnetwork represents the IoMT's brain and nerves. It sends data collected through the perception layer across wireless communication systems, and various specialised networks in a synchronous, accurate, trustworthy, and obstruction unrestricted manner. The examination sub-stage is principally in charge on the merging assorted networks along with numerous data types, information repositories, explanations, and other required data.

The application layer has two further sublevels: application for clinical data and applications for medical records in terms of decision-making. Medical data applications include, among other things, patient information management, medical equipment management, and material data management. The application of Medical data includes studies of patient record, diseases, drugs, diagnosis, therapies, and so on [24].

The key intention of this study, for monitoring heart illness in IoMT cloud architecture using enhanced salp swarm optimization with attention-based CNN.

The data are collected from patients' Wearable sensor devices, medical records, heart datasets, and diabetes datasets. The collected data is stored in a big data storage facility such as amazon 3 by the health-data storage level. The analytical layer preprocessed the data then classified with the proposed ACNN and SSO-LSTM. Finally, it moves to the data preparation layer whether the patient is to be monitored or not. From the Figure 2 we may depict the proposed mechanism on the heart monitoring system.

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

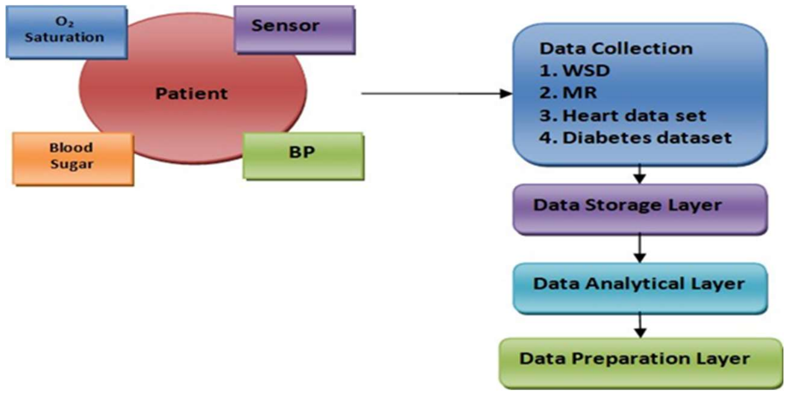

Figure 2: Proposed Workflow of the heart monitoring system

3.1 Data Collection and Description

To capture real-time data, IoMT based medicinal-sensors are place on the sicked-patient's body. The gender and age of the patient are stated right away. Using several IoMT medical sensors, examining various patient's medical changes have been recorded. To examine the patient's blood pressure, an upper arm blood pressure monitor is used. The fasting blood sugar was measured using a glucose monitor, the Medtronic IoMT sensor (glucose in the blood). The patient's heart rate is determined using a Sunroom electronics heartbeat IoMT medical sensor. A variety of IoMT medicinal-sensors like as medically-clever clothes, medically-clever watches, fitness trackers, etc., will be used towards real-time patient data acquistion. Figure 3 depicts how IoMT medical sensors are placed on a body of the patient to collect real-time data. The sicked-patient's health data are taken as of from a multiplicity of sources. The dataset is explained in full in Table 2. The data from the patient is collected using IoMT medicinal-sensors and Procedure 1(algorithm).

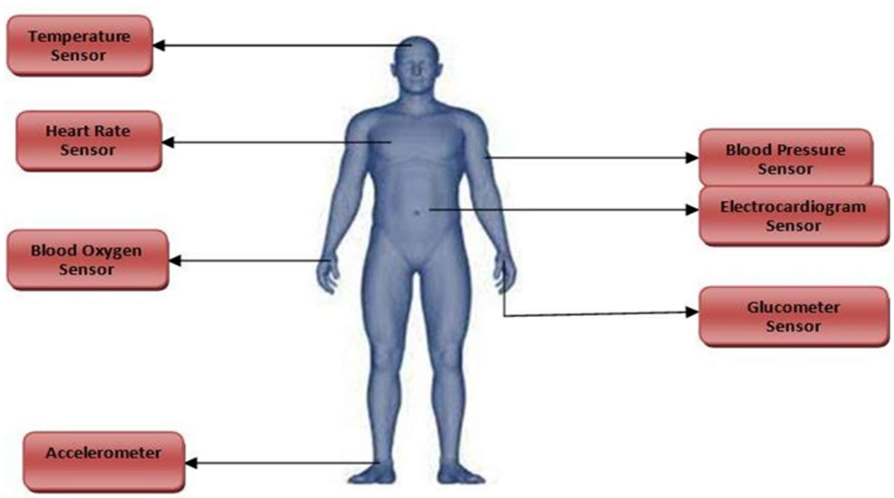

Figure 2: IoT Medical sensors on patient's data

The suggested framework model uses data from three different sources to track and offer patient health information: WSD, MR, heart dataset, and diabetes dataset. The WSD monitors each patient's physical indicators, like human-heart rate, human- blood pressure, and sugar level in the blood, in order to gather real-time body health signals that are important for effective

healthcare. The MR includes the patient's medical history, including details about their drinking, smoking,

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

and dyspepsia, as well as any prescribed medications. These records are highly helpful for assessing and identifying the patient's BP and diabetes-related medical issues. The information is gathered through the heart dataset, diabetes dataset, MR, and WSD.

Algorithm 1: Data Acquisition for IoMT medicinal-sensors (Client)

```
Import: Socket as skt
Input: medicinal Sensor
Output: Trigger Bit (tb)
Start SEN (Collection of data)
aclient ← (IPhost, sport_address)
aserver ← (IPserver, rport_address)
buffer (size) ← 2048
skt.bind(aclient , aserver)
while 1 do
times ← localtime()
data ← encode (sens-input)
skt.send(input)
input ← skt.receive ( )
if decode (input) == True then
Raise.Alert()
 End if
timer ← ltime()
delay = tr - ts
End while return (0)
End
```

3.1.1 Wearable Sensor Devices (WSD)

Mobile usage has significantly increased recently, along with the number of health-related applications. However, the data on smartphones is incredibly unreliable, making it challenging to manage sensitive data. As a result, we used WSD to extract data that might be used to track medical progress. Smart sensors and wearable technologies stay for the collection of the body signals of the sicked-patient's body includes human-heart rate, human-blood pressure, and sugar level in the blood in actual-time for observing their physiological state. Examples of these gadgets include wearable ECG sensors, pulse oximeters, glucometer sensors, and blood pressure monitors. In the proposed system, WSDs are fixed into the patirnt body to monitor how their bodies are functioning.

3.1.2 Medical records (MR)

MR gives details on the lab testing, medication intake, and patient treatments used in the treatment of high blood pressure and diabetes in patients. These records are evaluated to gather the information that can help doctors make better recommendations for people with high blood pressure and diabetes. The MR is massive in capacity, though, and each record has a lot of high- dimensional data in it.

High blood pressure and blood sugar patients may also be at risk for conditions like cardiovascular disease, renal disease, eye problems, neuropathy, and skin issues. In order to determine whether the patients have the aforementioned diseases and to track their development with more in-depth tests, the medical records should be studied. The various parameters that were gathered from WSD and MR are exposed in Table 2, data is described using table 3.

Table 2: Parameter for WSD and MR

DATA	NAME OF THEID	PARAMETER	JUSTIFICATION
WSD	WSD1	Age	Number of years in years
	WSD2	Sex	Predicting the gender, Male =1,
			Female = 0
	WSD3	ECG sensor reading	Utilization of ECG
	WSD4	BP	Blood Pressure in mmHg
	WSD5	Sugar level in Blood	Blood sugar mg/dl
	MR1	Sugar level in Blood	Patient’s blood test
	MR2	Cholesterol	Patient’s blood test

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

	MR3	Smoking	Yes or No
	MR4	Family history	Information about Diabetes/heart disease taken from their family history
	MR5	Cigarettes	Number of cigarettes per day
	MR6	Indigestion	Yes or No
	MR7	Drugs intake	Taken from a prescription of patients
	MR8	Diagnosis of heart disease	Status of angiography

Table 3 : Data Description

S.No	Feature Name	Description of feature
1.	Age	Age of patient
2.	Cpt	Types of chest pain
3.	Restecg	ECG sensor resting value
4.	Thal	Values of heart rate at rest
5.	Trestbps	BP at resting
6.	Chol	Patient Cholesterol
7.	Fbs	Blood sugar at fasting
8.	Ca	Major vessels number
9.	Thalach	Maximum achieved value of heart rate
10.	Sex	Gender type
11.	Slope	Slope related to peak of exercise
12.	Oldpeak	ST depression included from exercise w.r.t rest
13.	Exchange	Exercise-induced angina

3.1.3 Heart dataset

The heart data set get from the UCI machine knowledge source have 303 instances with 75 attributes. The elements employed in this dataset are sex, age, blood pressure, Sugar level in Blood, history of smoking, cholesterol and personal antiquity of artery diseases [33].

3.1.4 Diabetes dataset

Twenty parameters make up this dataset, including the date, code, time, Blood glucose measurement for pre-breakfast and post-breakfast, usual insulin dose, symptoms of hypoglycemia, and daily routine of exercise activity. This dataset includes the timestamp for events like breakfast, lunch, dinner, and bedtime. According to their inputs, such as their blood sugar levels before and after breakfast, regular insulin dosage, and regular exercise habits, diabetes patients can be categorized using this information [34].

3.2 Data storage Layer:

The suggested system will track patients' health conditions and give relevant information using three main sources of data. Because it is challenging to keep huge volumes of data, the WSD data and medical records are saved in the cloud. The data must therefore be stored in a big storage like Amazon S3 so that it can be accessed from anywhere at any time [25]. The data analytics layer receives the stored data for additional processing.

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

3.3 Data Analytical Layer

3.3.1 Preprocessing

From the IoMT medicinal sensors, data values will be aggregated for the reduction of noise or replace missing data by the preprocessing step. Data that is free of noise is necessary to detect patterns linked to heart disease effectively. Since the relationship between the data is calculated during the data collection, undesired or noisy data are removed using the median sample and sampling residual method. Figure 3 shows the working process of the data analytical layer.

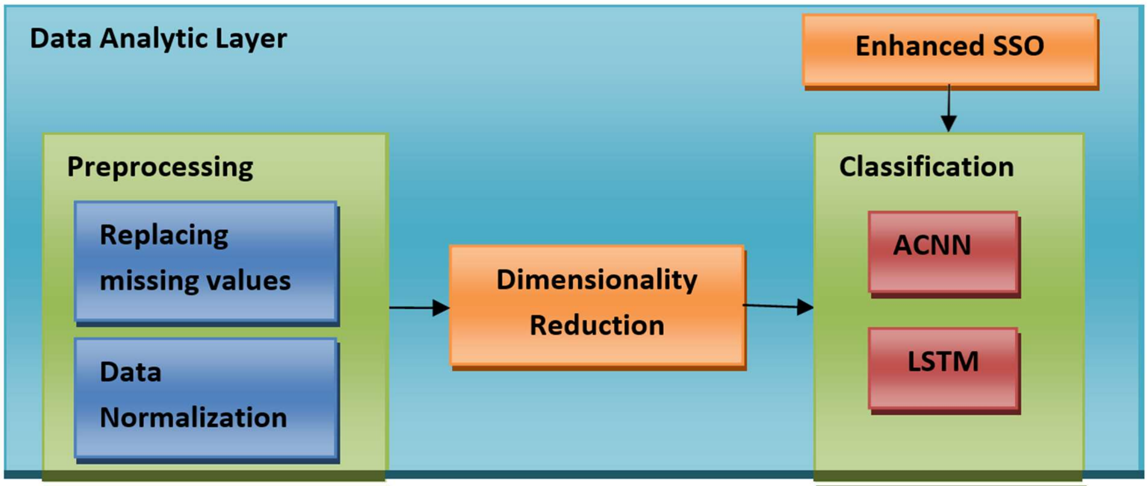

Figure 3: Data Analytical Layer The way of identifying heart disease is improved by this noise removal process.

1) Replacing Missing Values: Reviewing the dataset's data in order to calculate the mean of the lost data's exists the first stage. The mean value is identified by first logically ordering the data, and then computing the average values. A medium value is used to replace missing and unnecessary values.

2) Data Normalization: The data should be normalized in between from 0 and 1 once the missing values have been eliminated in order to make it simpler to evaluate the method of heart illness. The residual sampling technique is used based on calculating the standard deviation [7]. Regression analysis and different data distributions are used to normalize the data to predict heart disease. The regression equation for data normalization is shown in Equation (1) [7]:

$$P = \beta_0 + \beta_i Q + \varepsilon_i,\ for\ i = 1,2,3, \dots..n \tag{1}$$

Every two random data's are fits into the aforementioned model. The regression model in Equation (2) is given below:

$$P_i = \beta_0 + \beta_i Q + \in^* \tag{2}$$

The expression for the sample of the data are mentioned using the relation (2) with data-variance and data-error is $\in i$. Values of the least squares are denoted by $\beta 0$ and $\beta 1$ individually. The residual value, denoted by, is determined using equations (1) and (2). With the help of example data, the deviation is determined and average values. Average value are predicted in equation (3):

With variance and error, the expression for the sample of the data are expressed in equation (2) is $\in i$. The letters $\beta 0$ and

$\beta 1$respectively, stand for the values of the least squares. The residual value is expressed in the relation (1) and (2) are used in the determination of the outstanding value, denoted by (2). The samples of data then mean values are used to calculate the variation of the data. Mathematical relation (3)'s determines average value as follows:

$$\mu = \frac{\sum_{i=1}^{n} Q_i}{N} \tag{3}$$

where N denotes data frequency and Qi denotes the input data. Equations (4) and (5) give the data

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

normalisation formula:

$$n_r = \frac{\epsilon_i^*}{\sigma_i^*} \quad (4)$$

$$n_r = \frac{Q_i - \mu_i^*}{\sigma_i^*} \quad (5)$$

where,

$\in_i^*$ represents residual value and σ_i^* represents the variance

3.3.2 Enhanced Salp Swarm algorithm

The salp swarm algorithm was first introduced in 2017 [23] by Mirjalili et al. This programme imitates the way the sea salps forage for food. SSA imitates salps' swarming and navigational performances. Salps need a see-through body that resembles a bottle. For the purpose of navigating and foraging, they build chains of salps in the ocean. There is a leader salp and followers (also known as salps) in the chain. Through bearing-definition for looking for a decent food source in a multi-dimensional exploration area, the leading salp guides the followers. The algorithm runs iteratively and begins with a few random solutions. Each salp iteratively examines and uses the search space. At the conclusion of each iteration, the salp that fits its fitness the best is found. Using, the leader salp's position is modified (1). It is based on how far a food source is from the salp. Figure 4 shows the flowchart for the salp swarm algorithm (SSA) and its pseuocode be present on algorithm 2.

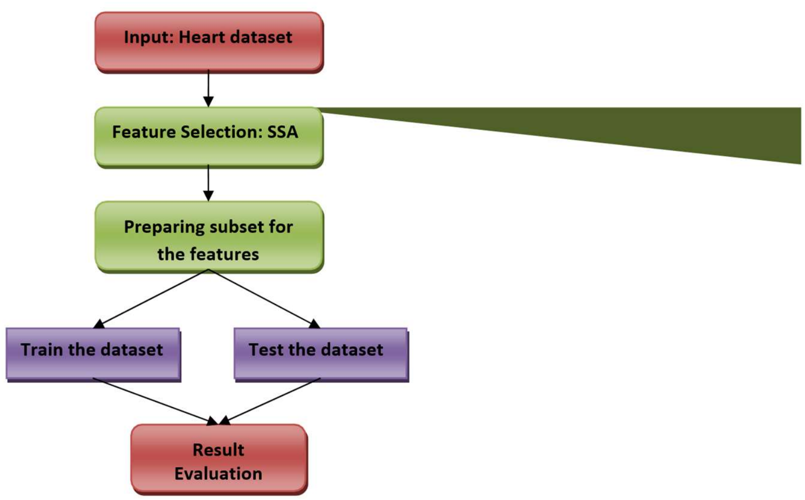

Figure 4: Flowchart of proposed Salp Swarm Algorithm (SSA)

Prerequisites: Parameters initialization for number of salps, number of iterations, the best position of salp, and value of best fit

Algorithm 2: Pseudocode of proposed Salp Swarm Algorithm (SSA)

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

Creating salps randomly
Evaluate the fitness of every salp
Assign the iteration value as 0
Update the value of s1
For every salp do
If i==1,
update the leader position
else
update the follower position
Perform the evaluation of fitness
If found the fitness solution, update fitness value
Current iteration is incremented
Repeat the for loop till the perform the maximum iterations
Return the optimized solution and its fitness value.

$$A_i^1 = \{FD_i + r_1((u_i - l_i) * r_2 + l_i)\ r_3 \geq 0\ FD_i - r_1((u_i - l_i) * r_2 + l_i)\ r_3 < 0 \quad (6)$$

Here,

A_i^1 denotes the leader's position at position i, FD_i denotes the location of the food source at position i, u_i and l_i denote the upper and lower boundaries at position i and r_1, r_2, r_3 denotes some random integers. r_1 uses to govern the exploration and exploitation.

$$r_1 = 2e\left(\frac{4i}{I}\right)^2 \quad (7)$$

Here, I characterize present repetition and I represent the total iteration

$$A_i^j = \frac{1}{2}(A_i^j + A_i^{j-1}) \quad (8)$$

Here A_i^j represents the present spot of j[th] follower in i[th] dimension

Using the Root Mean Square Error (RMSE) delivered in relation (8), the fitness value is calculated (9).

$$Fit = \frac{1}{2}\sum_{i=1}^{x}(H_i - H'_i)^2 \quad (9)$$

where x stands for the swarm's population, Hi, and H' I for predictable and definite value. When fitness is at its lowest point, the best solution can be found. Equation (10) is used to update the follower position.

$$Q_c^v = \frac{\hat{}}{2}(Y_t^2 + B_0 t) \quad (10)$$

Eqn can be used to express the FS updated location when Bo denotes the initial speed and t denotes the time, $Y = \frac{B_{fnl}}{B_0}$ and $B = \frac{Q - Q_0}{t}$, when B = 0. (11)

$$Q_c^l = \{\sigma S_c + a_1((t_c - u_c)a_2 + u_c), a_3 \geq 0\ \sigma S_c - a_1((t_c - u_c)a_2 + u_c), a_3 < 0$$

(11)

$$Q_c^v = \frac{1}{2}(Q_c^v + \sigma Q_c^{v-1}) \quad (12)$$

The predetermined iterations are computed till to find the perfect hyperparameter for LSTM, whichever comes first, the process of changing the sap's location will proceed repeatedly. Low, normal, and high blood pressure are just a few of the abnormal conditions that the softmax function is used to categorize in order to predict in patients. Other abnormal conditions include mental health, low side effects from drugs, normal side effects from drugs, and high side effects from drugs (stressed, depressed, happy, and normal). Using Equation 13, one may find the softmax function.

$$S_{max}^s = \frac{exp(L^s)}{\sum_c^k exp(L^s)} \quad (13)$$

where Ls and s stands for the corresponding feature category and time step c input. The medical

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

classification system for patients' blood pressure and diabetes is shown in Table 4.

Table 4 : Conditions for Diabetes and BP patients

Classification	Type	Sex	Blood sugar	Heart Rate	BP(mmHg)
Diabetes	Low	M/F	100<=125	140<=160	-
	Normal	M/F	<=99	60-80	-
	High	M/F	>126	>160	-
Blood Pressure	Low	M/F	-	-	<90
	Normal	M/F	-	-	90<=119
	High	M/F	-	-	>140

3.3.3 FC-deep LSTM

Next, the preprocessed data are specified in the direction of Fuzzy clustering for dimensionality minimization. Huge data quantities can be decreased via FC based on the characteristics of the data. To forecast patients' illnesses, the LSTM approach accurately categorizes organized and un-organized healthcare data. Big data are obtainable in factual-period when there are noise, size, format, and feature discrepancies. Accurate data collection for the health monitoring system is consequently more difficult. These problems are addressed by the FC-Enriched SSO-LSTM, our recommended solution.

FC-based dimension reduction, it uses FC to group patient data into groups according on how similar their illnesses are, such as diabetes, blood pressure, drugs consumed, other diseases, and side effects. Clustering is a crucial stage in the dimensionality reduction process that divides the data into groups based on a similarity metric [32]. The minimizing of an objective function is the foundation of FC. Eqn calculates the separation between the objective functions (14).

$$F(v,y) = \sum_{k=1}^{v} \sum_{i=1}^{n} (Q_{ki})|T_i - V_k|^2 \tag{14}$$

where Qki symbolizes rate of item i in the kth cluster, satisfies subsequent condition: where Vk denotes the centre of the cluster, y symbolizes the real number which is always higher than 1, Ti denotes the data measurement interms of i.

$$\sum_{k=1}^{v} Q_{ki} = 1; \ 0 \leq Q_{ki} \leq 1 \tag{15}$$

The cluster center can be determined using Eqn. (16).

$$v_t = \frac{\sum_{l=1}^{N} (Q_k)^y T_i}{\sum_{l=1}^{N} (Q_k)^y} \tag{16}$$

The cluster centre, which can be identified using Equation 16, is used to estimate the membership function.

$$Q_{ki} = \frac{1}{\sum_{l=1}^{N} \left(\frac{|T_i - V_k|}{|T_i - V_s|}\right)^{\frac{1}{v-1}}} \tag{17}$$

The output clusters, sometimes referred to as the membership function, are provided by Equation (17). The membership stacks determine how many clusters the user needs.

The output clusters, sometimes referred to as the membership function, are provided by Equation (17). The membership stacks determine how many clusters the user needs.

3.3.4 The ACNN-LSTM Based Classification's Process.

The ACNN-LSTM model is used in conjunction with the best feature selection to carry out the classification procedure. In this study, LSTM and CNN techniques were used in a hybrid fashion. In the processing of the sequential data, RNN will be often employed. From most recent input, in addition to the prior output may merged. Dealing with LSTM problems might be made simple by several gates. The input can be randomly memorized using the the LSTM gate architecture [23]. Along with the most significant knowledge, the least important knowledge is completely forgotten. Therefore, the precise data can be

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

maintained in the current state. The input is the sigmoid function, which generates a value between 0 and 1, selecting the data that is currently being retained. Its inputs are the output of earlier stage h and the existing response of a function X t. (t-1). To retrieve the following state's h t hidden layer, the response and forgotten gates may be employed, which are also used to start the comprehensive state from the foregoing unit outputs. The cell state produced aimed at exploring an outcomes and it is showed as t, in which the sigmoid function yields in the range between 0 to 1. When ot causes the multiplication of cell stated dataset, the tan h layer has been used to activate it. Therefore, the LSTM determination's output details are modeled. For the LSTM, the following equation (18-23) arithmetically expresses the many relationships between the various gates:

$$z_t = tanh\ (W_z[h_{t-1}, x_t] +\ b_z \quad (18)$$

$$i_t = sigmoid\ (W_i[h_{t-1}, x_t] +\ b_i \quad (19)$$

$$f_t = sigmoid\ (W_f[h_{t-1}, x_t] +\ b_f \quad (20)$$

$$O_t = sigmoid\ (W_0[h_{t-1}, x_t] +\ b_0 \quad (21)$$

$$C_t = f_t * C_{t-1} +\ i_t * z_t \quad (22)$$

$$h_t =\ O_t * tanh\ (C_t) \quad (23)$$

As there is increase in length of the input sequence, it is very harder to the explosion of gradient problematic. Through input gate demonstrate on in what way to overlook the information of the cell state,, but forget gate demonstrates on how to measure the unique input. The output may be measured using the cell's current state and contents of the current state. The CNN-LSTM methodology suggested for four different networks on behalf of constantly providing a massive amount of embedding labels in order to acquire diverse feature qualities.

$$c = conv(X, K) +\ b \quad (24)$$

The symbol x may utilized to denote the length of the data-sequence. The acronym LSTM stands to refer to combined LSTM process (x). For aforementioned goals, parallel as well as series architectures are used by both the CNN and LSTM-NN. The RNN is frequently used to process the sequential data. The RNN combines the furthermost input and the most current output commencing the earlier repetition. A network of several gates could be used to quickly solve LSTM problems. In general, due to the nature of the convolutional approach, the series arrangement is extensively used regardless of the data loss. Parallel structures are now used in place of series structures to get effective results. The structure can be recorded in all channels in the following ways:

$$channel(x) = [conv(x) \oplus LSTM(x)] \quad (25)$$

With x denotes the input and the output, articulated as c_{out} and w_{out}

$$C_{out} = channel_{embedding} = v_w(x) \quad (26)$$

$$W_{out} = channel_{embedding} = v_c(x) \quad (27)$$

The 4-channel mechanism's output result and interpretation are combined by way of a hidden layer output.

$$h = [C_{out} \oplus W_{out}] \quad (28)$$

The hidden layer outcomes be located then sent to the FC layer, and finally, the Softmax layer is applied to the output of the classifier as follows:

$$\hat{y} = softmax(dense(h)) \quad (29)$$

The descriptions of the demonstrations with the help of all four channels are provided below. Dynamic flexible weight structures' crucial component, the w weight score, is represented as follows:

$$e_i = v_a^T\ tanh\ (W_r h_i +\ b) \quad (30)$$

$$h_i = \langle h_t' : c_t \rangle \quad (31)$$

When the hidden layer outcome is represented by hi and the LSTM outcome by ht ′, respectively, In LSTM, ct stands for the state,

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

[a] for an arbitrary initiation vector, [b] for an arbitrary bias, and Wr for an arbitrary initiation weight matrix.

$$w = \frac{exp\,(e_i)}{\in} [\sum_{k=1}^{T_x} \quad exp\,(e_i\, k)] \tag{32}$$

Although x can be used to indicate the sequence length, dynamic adaptive weight has weighed the resulting vector ci as

$$c_i = \sum_{j=1}^{T_x} \quad w.h_j \tag{33}$$

3.4 Data presentation layer

In the presenting layer, the doctor assesses the patients' health status using the outcome of the enhanced SSO-LSTM. Table 5 classifies pharmaceutical results according to patient mental health.

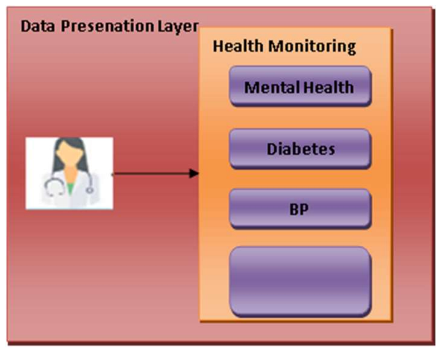

Figure 5: Data Presentation layer

Table 5: Prediction of illness effected – patient's psychological health an drug's side effects

	Category	Post sentimental	Drug's sentimental
Mental health	Normal	Neutral	-
	Happy	Positive	-
	Stressed	Highly negative	-
	Depressed	Negative	-
Prediction of drug's side effect	NSE	-	Positive
	SE	-	Positive
	LSE	-	Neutral

4. RESULTS AN DISCUSSIONS

In the training phase, the collected datas are preprocessed and the features are selected. The selected features are classified by using attention-based CNN and the LSTM. In the training phase the performance is evaluated and predicted whether the patient needs to be monitored or not. The training and testing phase are depicted by figure 6,figure 7.

Figure 6: Training Phase

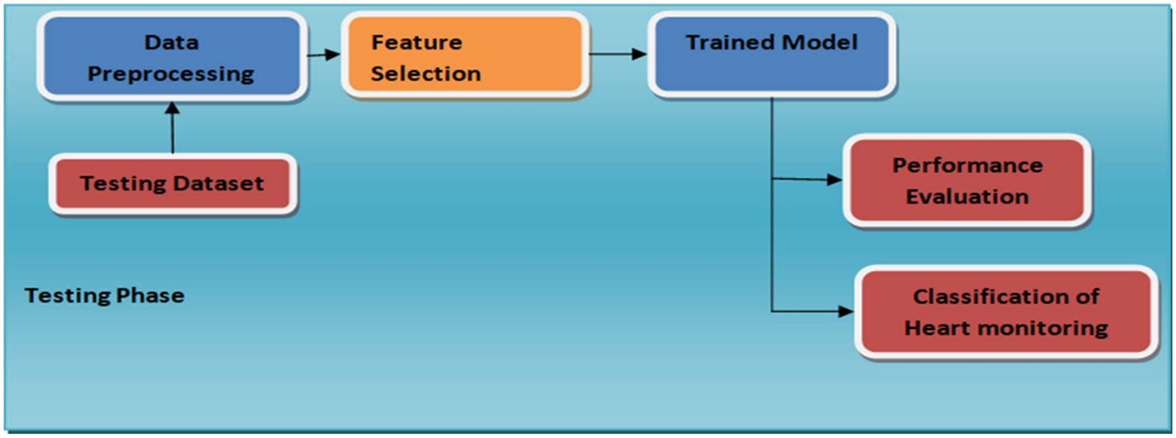

Figure 7: Testing Phase

4.1. Simulation setup

Python is used to simulate the proposed FC-SSOLSTM implementation. The learning rate ,epoch and batch size for LSTM are, in that order, 0.0001, 32, and 30.

4.2. Metrics for evaluation

Performance measurements including accuracy, recall, mean absolute error (MAE), F-measure, root mean square error (RMSE), and precision are evaluated using the six metrics.

Accuracy: This metric, which is given in Equation 34, is used to determine how accurately all samples are categorised.

$$AC = \frac{T_{po} + T_{Ne}}{T_{po} + T_{Ne} + F_{po} + F_{Ne}} \quad (34)$$

Precision: It refers to the classification's precision. As seen in Equation 35, greater precision entails fewer errors.

$$PN = \frac{T_{po}}{T_{po} + F_{po}} \quad (35)$$

Recall: Equation 36 calculates the recall or sensitivity of the number of appropriately categorized examples.

$$Recall = \frac{T_{po}}{T_{po} + F_{Ne}} \quad (36)$$

F-score: According to Equation 37, the F-score is defined as the weighted average of precision and recall, which together adds recall and precision.

$$F - Score = 2 * \frac{P_{PN} * R_{RL}}{P_{PN} + R_{RL}} \quad (37)$$

4.3 Evaluation of the performance

With regard to processes like data-precision, accuracy in data, data-recall, F-score, MAE, and RMSE, proposed SSO- LSTM is tested on four datasets and contrasted with established techniques like DMBi-LSTM [26], SLSTM [27], and EDLM [28]. The accuracy of the suggested SSO-LSTM and popular approaches are contrasted in Fig. 8. Due of the volume and variety of the big data, the current approach cannot handle it. To address these challenges, our proposed SSO-LSTM approach with the help of fuzzy clustering in the minimization of the volume by clustering the significant facts. As a consequence, the suggested SSO-LSTM (95%) approach and the proposed ACNN have 93% high accuracy for dataset-1 when compared to existing techniques like DMBiLSTM (70%), EDLM (64%) and SLSTM (82%). When compared to other methods for dataset 4, such as DMBi-LSTM (70%), EDLM (67%) and SLSTM (89%) the accuracy of the proposed SSO-LSTM and ACNN is 95%. According to the analysis above, our

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

suggested SSO-LSTM has a high level of accuracy when compared to other methods for datasets 1 through 4.

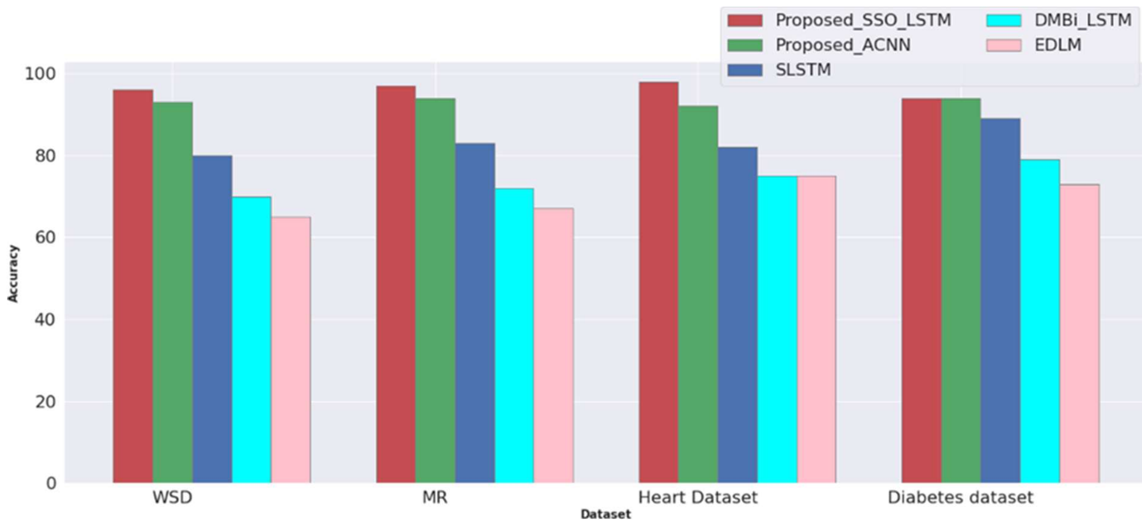

Figure 8: Comparison on proposed data-accuracy on existing work

The comparison of precision using the suggested SSO-LSTM, ACNN, and standard approaches is shown in Fig. 9. The LSTM network's hyper-parameters are optimized using the SSO, and an upgraded neural network (SSO-LSTM) system employed for determining that the illness effected person is healthy or un-healthy. An outcome demonstrates for the dataset-1, the suggested SSO-LSTM (93%) and ACNN (89%) techniques have higher precision than more widely used methods like DMBi-LSTM (50%) and SLSTM (78%). When compared to existing methods like 79% is achieved using EDLM , 62% has been achieved using DMBi- LSTM, and 83% has been achieved in SLSTM for dataset-4, the suggested SSO-LSTM has a 90% accuracy rate. In light of the research above, it is evident that our suggested SSO-LSTM has excellent precision when compared to other methods for datasets 1 through 4.

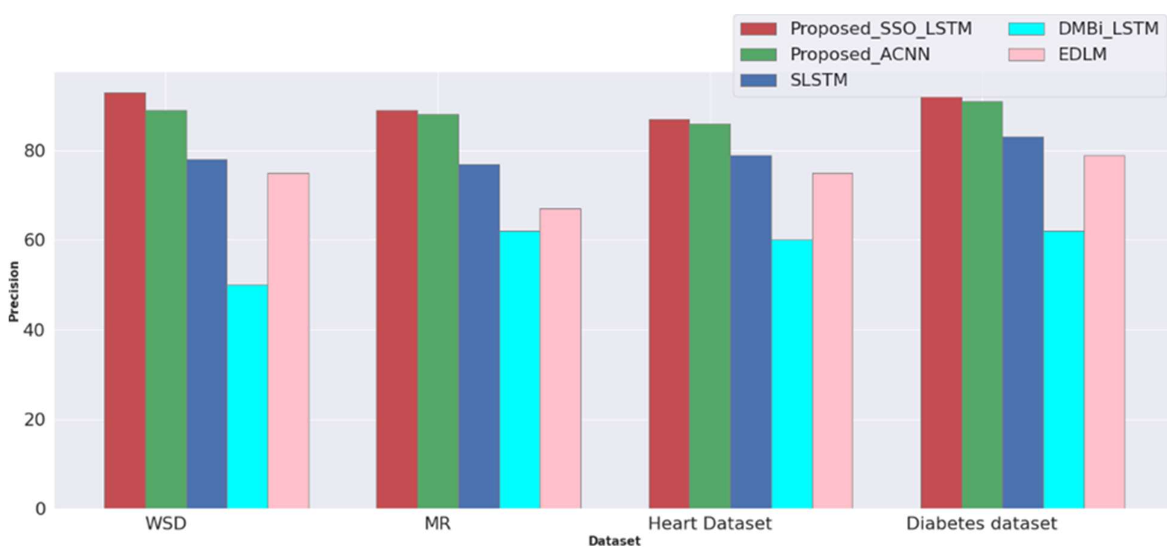

Figure 9: Comparison on proposed data-precision on existing work

Figure 10 compares recall to the suggested SSO-LSTM and the conventional methods. During the preprocessing stage, the data are transformed using the low-high normalisation prototype. Measuring actual-data down to a little range for processing and it helps the suggested SSO-LSTM method in the direction of decrease a huge dataset to a small dataset by scaling dataset towards a certain constrained

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

choice. As a consequence, for dataset-1, the suggested SSO-LSTM (85%) and proposed ACNN (89%) approaches outperform other popular techniques like DMBi-LSTM (40%), EDLM (75%) and SLSTM (78%) methods in terms of recall. In contrast to other methods like DMBi-LSTM (49%), EDLM (74.53%), and SLSTM (82%), the suggested SSO-LSTM has a recall of 92% and the proposed ACNN has a recall of 90% for dataset 4. It is clear from the analysis above that for datasets 1 through 4, our proposed SSO-LSTM has a high recall in comparison to other techniques.

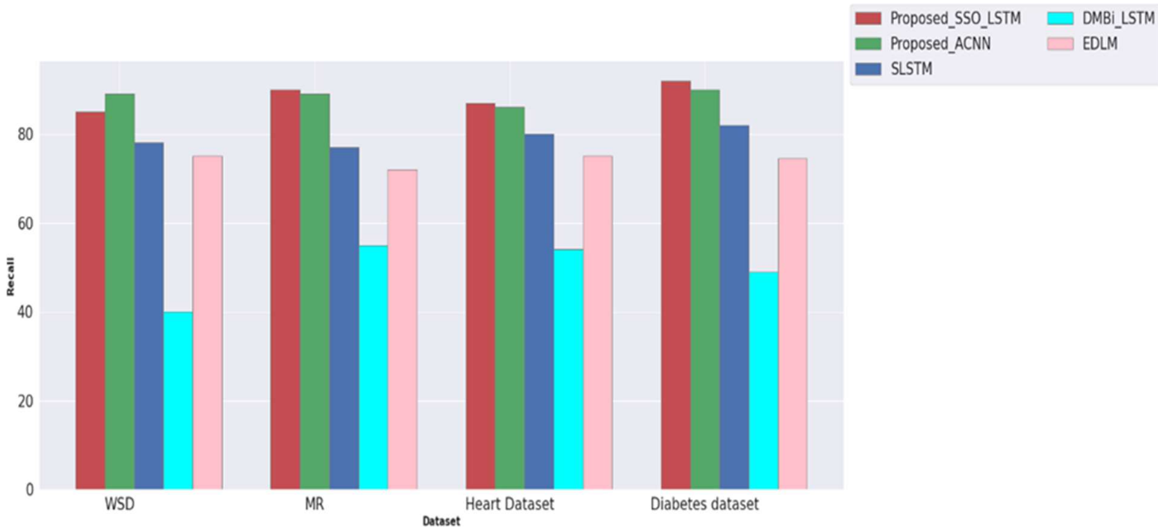

Figure 10: Comparison of the proposed recall with an existing work

Figure 11 provides a comparative analysis of a F-measure with the new SSO-LSTM and traditional approaches. The HAVF filter in the suggested SSO-LSTM technique can remove noise brought into the information during the data transformation process. On comparison towards to related work like DMBi-LSTM, EDLM, and SLSTM, our suggested SSO-LSTM has a high F-measure because the noise reduction does not eliminate any MR features. According to dataset-1, the F-measure scores for the DMBi- LSTM, EDLM, SLSTM, proposed ACNN, and proposed SSO-LSTM are 45%, 54%, 70%, 52%, 40%, 79%, and 80%, respectively. In comparison to current techniques such as 42% of DMBiLSTM , 49.8% of EDLM, and 88% of SLSTM , the proposed SSO- LSTM has an F-measure of 90%, while the proposed ACNN has an F-measure of 89% for dataset-4. The analysis above shows that our suggested SSO-LSTM has a high F-measure when compared to other approaches aimed at datasets 1–4.

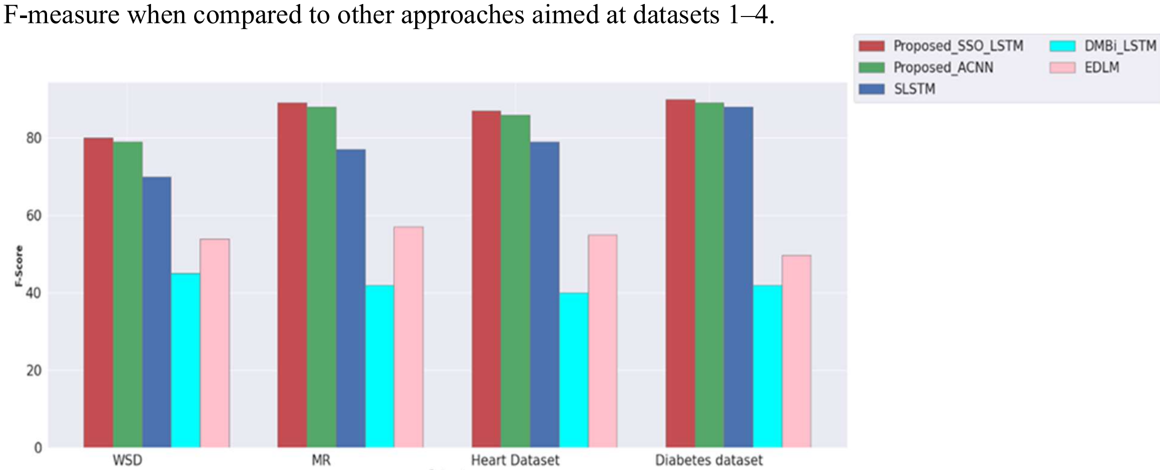

Figure 11: Comparison of the proposed F-Score with an existing work

5. CONCLUSION and FUTURE ENHANCEMENTS

In this research-paper, for the Chronic disease, the human-health Care Observing Arrangement will be designated. It has four tiers of the suggested method are data collection, storage of the data on basis cloud storage technique, analytics of data, and the various presentation levels. The categorization is done using the improved SSO-LSTM and ACNN. The cloud storage layer stores the data that is gathered from the WSD, MR, heart disease, diabetes, and databases. The vast amounts of data are saved in the on basis cloud storage stages. On data manipulation stage, normalisation is used to do pre-processing on the WSD, MR, heart disease, and diabetes datasets. The min-max normalisation approach is used in the data processing and collecting processes. Diabetes, heart disease, and MR datasets are cleaned up using filtering techniques. Next, during preprocessing, normalisation and value replacement are performed. The data are given to the dimensionality reduction process. The data-dimensional minization procedure makes use of FC. Huge data quantities can be decreased via FC based on the characteristics of the data. To predict patients' stages of illness, the LSTM procedure accurately categorizes organised and formless healthcare data. Enhanced SSO is used to identify the hyper- parameters of the LSTM prototype that should be set to their ideal values. For the categorization, upgraded SSO-LSTM and ACNN are both utilised. The doctor next decides patient is well or ill established on the advanced SSO-arrangement LSTM's outcomes in the presentation level. The findings of this study can be used to the routine monitoring of blood pressure and diabetes using data on patient health from government organisations that visit a lot of people. In the future, it is planned to work on improving the monitoring system with deep learning based prototypes and provide it as a mobile application. For illness affected persons who reside in rural, proposed strategy is highly useful.

REFERENCES

1. World Health Organization, (2020) Cardiovascular Diseases, WHO, Geneva, Switzerland, https://www.who.int/healthopics/cardiovascular-diseases/#tab=tab_1. Accessed 9 May 2021.
2. D. Shah, S. Patel, and S. K. Bharti, "Heart Disease Prediction using Machine Learning Techniques," SN Computer Science, vol. 1, no. 6, 2020, doi: 10.1007/s42979-020-00365-y.
3. H. F. Kareem, M. S. A.-Husieny, F. Y. Mohsen, E. A. Khalil, and Z. S. Hassan, "Evaluation of SVM performance in the detection of lung cancer in marked CT scan dataset," Indonesian Journal of Electrical Engineering and Computer Science, vol. 21, no. 3, pp. 1731-1738, 2021, doi: 0.11591/ijeecs.v21.i3.pp1731-1738.
4. K. M. Almustafa, "Prediction of heart disease and classifiers' sensitivity analysis," BMC Bioinformatics, vol. 21, no. 1, doi: 10.1186/s12859-020-03626-y.
5. H. Jindal, S. Agrawal, R. Khera, R. Jain, and P. Nagrath, "Heart disease prediction using machine learning algorithms," IOP Conference Series: Materials Science and Engineering, vol. 1022, 2021, p. 012072, doi: 10.1088/1757- 899x/1022/1/012072.
6. G. Saranya and A. Pravin, "A comprehensive study on disease risk predictions in machine learning," International Journal of Electrical and Computer Engineering, vol. 10, no. 4, pp. 4217-4225, 2020, doi: 10.11591/ijece.v10i4.pp4217-4225.
7. H. David, Benjamin, and S. Belcy, "Heart disease prediction using data mining techniques," 09. ictact journal on soft computing, October 2018, vol. 09, no. 01, 2018, doi: 10.21917/ijsc.2018.0253.
8. H. A. Lafta, Z. F. Hasan, and N. K. Ayoob, "Classification of medical datasets using back propagation neural network powered by genetic-based features elector," International Journal of Electrical and Computer Engineering, vol. 9, no. 2, pp. 1379-1384, 2020, doi: 10.11591/ijece.v9i2.pp.1379-1384.
9. P. K. Sahoo and P. Jeripothula, "Heart Failure Prediction Using Machine Learning Techniques,"

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

SSRN Electronic Journal, 2020, doi: 10.2139/ssrn.3759562.
10. [10] L. Yang et al., "Study of cardiovascular disease prediction model based on random forest in eastern China," Scientific Reports, vol. 10, no. 1, 2020, doi: 10.1038/s41598-020-62133-5.
11. A. Ibrahem, R. A. Ahmed, M. A. Mohialden, and Y. M. Ali, "Efficient method for breast cancer classification based on ensemble offending tree and naïve Bayes," Indonesian Journal of Electrical Engineering and Computer Science, vol. 18, no. 2, pp. 1074-1080, 2020, doi: 10.11591/ijeecs.v18.i2.pp1074-1080.
12. M. F. Darmawan, A. F. Z. Abidin, S. Kasim, T. Sutikno, and R. Budiarto, "Random forest age estimation model based on length of left hand bone for asian population," International Journal of Electrical and Computer Engineering, vol. 10, no. 1, pp. 549-558, 2020, doi: 10.11591/ijece.v10i1.pp549-558.
13. M. A. Khan, ''An IoT framework for heart disease prediction based on MDCNN classifier,'' IEEE Access, vol. 8, pp. 34717–34727, 2020, doi: 10.1109/ACCESS.2020.2974687
14. A. U. Haq, J. P. Li, M. H. Memon, S. Nazir, and R. Sun, ''A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms,'' Mobile Inf. Syst., vol. 2018, Dec. 2018, Art. no. 3860146, doi: 10.1155/2018/3860146.
15. M. Liu and Y. Kim, ''Classification of heart diseases based on ECG signals using long short-term memory,'' in Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Honolulu, HI, USA, Jul. 2018, pp. 2707 –2710, doi: 10.1109/EMBC.2018.8512761.
16. El Zouka HA, Hosni MM. Secure IoT communications for smart healthcare monitoring system. Internet of Things 2021;13:100036.
17. Ali F, El-Sappagh S, Islam SR, Kwak D, Ali A, Imran M, Kwak KS. A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Inf Fusion 2020;63:208–22.
18. Saini R, Kumar P, Kaur B, Roy PP, Dogra DP, Santosh KC. Kinect sensor-based interaction monitoring system using the BLSTM neural network in healthcare. Int J Machine Learning Cybern 2019;10(9):2529–40.
19. G. Reshma, C. Al-Atroshi, V. Kumar Nassa et al., "Deep learning-based skin lesion diagnosis model using dermoscopic images," Intelligent Automation & Soft Computing, vol. 31, no. 1, pp. 621–634, 2022.
20. Z. Al-Makhadmeh and A. Tolba, ''Utilizing IoT wearable medical device for heart disease prediction using higher order Boltzmann model: A classification approach,'' Measurement, vol. 147, Dec. 2019, Art. no. 106815.
21. T. Vivekanandan and N. C. Sriman Narayana Iyengar, ''Optimal feature selection using a modified differential evolution algorithm and its effectiveness for prediction of heart disease,'' Comput. Biol. Med., vol. 90, pp. 125–136, Nov. 2017.
22. K. Uyar and A. Ilhan, ''Diagnosis of heart disease using genetic algorithm based trained recurrent fuzzy neural networks,'' Procedia Comput. Sci., vol. 120, pp. 588–593, 2017, doi: 10.1016/j.procs.2017.11.283.
23. F. Ahmed, ''An Internet of Things (IoT) application for predicting the quantity of future heart attack patients,'' Int. J. Comput. Appl., vol. 164, no. 6, pp. 36–40, Apr. 2017, doi: 10.5120/ijca2017913773.
24. Sun, L.; Jiang, X.; Ren, H.; Guo, Y. Edge-Cloud Computing and Artificial Intelligences in Internet of Medical Things: Architectures, Technology and Applications. IEEE Access 2016, 8, 101079–101092. [CrossRef]
25. Abdur Rahim Mohammad Forkan, Ibrahim Khalil, Zahir Tari, Sebti Foufou, Abdelaziz Bouras, A context-aware approach for long-term behavioural change detection and abnormality prediction

ISSN:2153-182X, E-ISSN: 2153-1838
Vol. 17 No. 02 (2023)

in ambient assisted living, Pattern Recognition, Volume 48, Issue 3, 2015, Pages 628-641, ISSN 0031-3203, https://doi.org/10.1016/j.patcog.2014.07.007.

26. Ali F, El-Sappagh S, Islam SR, Ali A, Attique M, Imran M, Kwak KS. An intelligent healthcare monitoring framework using wearable sensors and social networking data. Future Generat Comput Syst 2021;114:23–43.
27. Rabby MF, Tu Y, Hossen MI, Lee I, Maida AS, Hei X. Stacked LSTM based deep recurrent neural network with kalman smoothing for blood glucose prediction. BMC Med Inf Decis Making 2021;21(1):1–15.
28. Ali F, El-Sappagh S, Islam SR, Kwak D, Ali A, Imran M, Kwak KS. A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Inf Fusion 2020;63:208–22.
29. Kalpana Murugan,S. Murugeswari, J. P. Reddy, M. H. Chandra and P. V. Reddy, "Smart Medical Telemetry Acquisition System," 2021 Second IEEE International Conference on Electronics and Sustainable Communication Systems (ICESC),organized by Hindusthan Institute of Technology, Coimbatore held on 04.08.21 to 06.08.21. Published on IEEE Xploreon 23 September 2021, Print on Demand(PoD) ISBN:978-1-6654-2868-2,pp. 1289-1297, doi: 10.1109/ICESC51422.2021.9532775. 2.
30. Kalpana Murugan, Sai Pavan K, Narendranath T , and Bhanu Chand S "An Adafruit Cloud-Based Health Monitoring Device Using IoT Technology" published in Advances in Intelligent Systems and Computing, Springer, 2021. ISBN: 978-981-16-7330-6. P.No. 15-27, https://link.springer.com/book/10.1007/978-981-16-7330-6.
31. Phong Thanh Nguyen, M. Lorate Shiny, K. Shankar, Wahidah Hashim, Andino Maseleno "Robotic Surgery" published in International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-8 Issue-6S2, August 2019, DOI:10.35940/ijeat.F1303.0886S219.
32. Thaha M.M., Kumar K.P.M., Murugan B.S., Dhanasekeran S., Vijayakarthick P., Selvi A.S."Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images" published inJournal of Medical Systems,2019, volume-43, Issue- 9, Art No-294, DOI-10.1007/s10916-019-1416-0. ISSN-1485598.
33. Shankar K., Elhoseny M., Chelvi E.D., Lakshmanaprabu S.K., "An efficient optimal key based chaos function for medical image security" published inIEEE Access,2018,Volume-6, Art. No-8528441, DOI-10.1109/ACCESS.2018.2874026, ISSN-21693536.
34. Shankar K., Elhoseny M., Lakshmanaprabu S.K., Ilayaraja M., Vidhyavathi R.M., A. Elsoud M., Alkhambashi M. "Optimal feature level fusion based ANFIS classifier for brain MRI image classification" published inConcurrency and Computation: Practice and Experience,2020, Volume-32,Issue-1,DOI-10.1002/cpe.4887,ISSN-15320626.
35. Pitchipoo P., Venkumar P., Rajakarunakaran S. "Fuzzy hybrid decision model for supplier evaluation and selection" published inInternational Journal of Production Research, 2013,Volume-51, Issue-13,DOI- 10.1080/00207543.2012.756592,ISSN-207543.