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RESEARCH ON SPEECH COMMUNICATION ENHANCEMENT OF ENGLISH WEB-BASED LEARNING PLATFORM BASED ON HUMAN-COMPUTER INTELLIGENT INTERACTION

YUFANG GU*

Abstract. This study presents a novel web-based learning platform that leverages human-computer intelligent interaction to enhance English communication skills. The platform integrates cutting-edge technologies to create an immersive learning experience, combining natural language processing, speech recognition, and interactive exercises. Learners engage in real-time conversations with virtual tutors, receive personalized feedback, and access a vast repository of educational resources. The platform not only facilitates language acquisition but also encourages self-paced learning, making it a valuable tool for both educators and students. By harnessing the power of artificial intelligence, this web-based platform represents a significant advancement in the realm of English language education. To overcome these issues this paper proposed SVM with an improved satin Bower bird optimization algorithm (SVM-ISBBO). SVM-ISBBO uses fog computing services that minimize the latency and speeds up the process, effectively handling huge wearable devices. In this proposed work SVM-ISBBO monitors the students communication, vocal parameters, blood pressure, etc, and these values are obtained from wearable sensor devices and their notifications are sent back to teachers. Teachers diagnosed the student information and sent back the alert notifications to the students for taking proper medications. All this information is stored in fog-based cloud storage in a secure manner. The accuracy rate of KNN got 78.56%, NB got 81.74%, SVM got 85.15% and the proposed work of SVM-ISBBO got 92.34%.

Key words: English communication, fog computing, SVM, Satin Bower Bird Optimization, web communication.

1. Introduction. Nowadays, due to technological advancements in the communication field monitoring the health status of students and maintaining communication management. And the transmission of English communication information via a proper wireless communication network in a secure manner is a challenge. By implementing algorithms, handling unstructured data, and producing organized output in report format like electronic documents with reports in a secure[8]. Communication monitoring information about students is obtained from various wearable sensor devices on communication servers digitally. Due to the rapid growth of technology, various attackers can attack the transmission of communication information to clinical information[19]. For monitoring student information remotely based on IoT technology and collecting the smart health information of student's physical and mental strength, living environment, lifestyle, hereditary communication issues details, etc. This IoT-based communication information is transmitted to a cloud storage computing service through the wireless network. from the cloud storage, teachers can monitor and diagnose students' health conditions and send notification messages like early prevention of disease and its corresponding treatment [14].

The communication cyber-physical system uses smart communication sensor devices, a wireless communication network, and managing the sensor signals generated from communication sensor devices. To implement the MCPS, various machine learning and deep learning algorithm are applied in the monitoring of communication English communication information[17]. Cyber-physical system detects attacks in the storage of communication information in cloud computing. The main objective of the CPS environment is providing the secure using an artificial intelligence-based environment [23].

L. Zheng et.al[24] presented a system for producing an alert signal at the early stage warning for high-risk students using deep learning algorithms and maintaining electronic health records. Shuwandy et al. [15] described that CPS embedded the sensor devices with IoT technology and stored the communication information in the cloud storage platform. Ahmad Ali AlZubi et.al [4] proposed that Cyber-attack detection in communication uses cyber-physical systems and machine learning techniques. Wazid et al[20] propose AI-based technology

*School of Foreign Languages Hubei Engineering University Xiaogan 432000 Hubei School of Grduate Studies Baliuag University Baliuag 3006, Bulacan, Philippines (guyufang@hbeu.edu.cn)

for the prediction of a cybercrime attack in communication information and it uses an edge-based IoT environment. In view of existing research work, the issues are inefficient in handling huge wearable sensor devices, and lack of detection of the attack in the storing of English communication information. To overcome these issues this paper proposed SVM with an improved satin Bower bird optimization algorithm (SVM-ISBBO). SVM-ISBBO uses fog computing services that minimize the latency and speeds up the process, effectively handling huge wearable devices. The main contribution of this work is:

1. Monitoring student communication level these values are obtained from wearable sensor devices and stored in a fog node-based cloud storage platform.

2. For monitoring the abnormal condition and providing secure storage of student health information in a fog node-based cloud storage platform by implementing SVM with the improved satin bowerbird optimization algorithm.

The paper has been organized as follows: Section 2 describes the review of the literature, Section 3 methodology of monitoring and secure storage of communication cyber-physical system-based student English communication information using SVM-ISBBO, Section 4 discusses the experimented results and Section 5 concludes the paper with future directions.

2. Review of Literature. In the IoT-based technology of cloud computing embedded computation resources, heterogeneous data structure, storage capacities, and high-speed processing have been included in the development of smart communication systems. This fog computing links the smart sensor devices with the cloud storage platform. It provides a quick response time, but the issue with cloud computing is the negative impact of handling real-time reactions[2]. Fog computing is used in the English communication system which includes three levels of processing namely data is collected from edge devices of sensors, multiple devices are interlinked with one another, and processing of collected sensor data takes less than a second with its decision-making process[16].

The smart English communication system has become popular in the earlier diagnosis of a disease which provides proper treatment to the student. At the same time, a smart communication system consists of various sensors with MRI, PET, CT, etc. In order to provide the best quality of treatment to the student as well as to control the spread of the virus smart communication system is required. This smart communication system is monitored by a web based monitoring system[3]. A. A. Mutlag et.al[12] described the concept of enabling the technologies for fog computing in communication IoT systems. Kontakt LS, et al [10] presented an accurate prediction of the speech issues of the student by applying the machine learning technique and securely storing health information in a cloud storage platform.Li , et al[11] described the handling of communication information from various communication sensor devices and analysis stored in cloud storage platforms as well as handling big data analytics.Wu et al [21] presented that cyber-physical systems are based on preserving and securely storing English communication information and also detecting malicious attacks in the CPS. Thamilarasu et al [18] proposed that detection of attack in the English communication information is stored in cloud computing and also the detection of attacks in IoMT.

3. Methodology. An effective communication cyber-physical system for monitoring and securely storing communication information using fog computing service based on SVM with improved satin bower bird optimization algorithm (SVM-ISBBO). This communication cyber-physical system integrates the various communication sensor devices and obtained the communication-based sensor information and stores it in a fog node-based cloud storage system in a secure manner. The framework of SVM-ISPBO is given in Figure 3.1.

Figure 3.1 contains three layers data collection layer, the communication data stored in fog node-based cloud storage layer, and the communication data information processing layer.

3.1. Data Collection Layer. From the student, communication sensor signal information is collected and stored in a fog node-based cloud storage system. This collected communication information is diagnosed by the teachers and updates the current health status of students via a mobile app. The wearable sensor devices which are used in the monitoring of the health status of the students are temperature sensors, blood pressure sensors, heartbeat sensors, ECG sensors, EEG sensors etc. This sensor information is collected via wireless communication. These sensor devices are embedded with ESP8266 Node MCU microcontroller[6]. It is high processing speed, low cost, and provides accurate results.

Table 2.1: Survey on the smart communication system in CPS

Author Name.	*Sensors used.*	*Description.*
Ahmed Elhadad et.al (2022) [1]	temperature,ECG, and blood pressure sensors	Communication Monitoring System for Managing the Real-Time Notification in a fog computing system.
S. Senganet.al (2022) [13]	temperaturesensor, Heartbeat sensor	Smart communication communication system for providing security devices on MIoT using Raspberry Pi
I. Ahmed et.al (2021) [1]	temperaturesensor, Heartbeat sensor	A deep-learning-based smart communication system for student discomfort detection at the edge of the Internet of Things
Al-Sheikh et.al (2020) [2]	Heart rate, ECG, and-body temperature sensor	Arduino, NodeMCU is used for transferring information via Wi-Fi.
Elangoet.al (2020)[7]	Heartbeat sensor, bodytemperature sensor,	Storing health information in NodeMCU edge devices and implementing the communication protocols of Wi-Fi/ HTTP, and MQTT.
Islam et al. (2020) [9]	Heartbeat sensor, bodytemperature sensor,	Storing health information in NodeMCU edge devices and implementing the communication protocols of Wi-Fi/ HTTP, and MQTT.

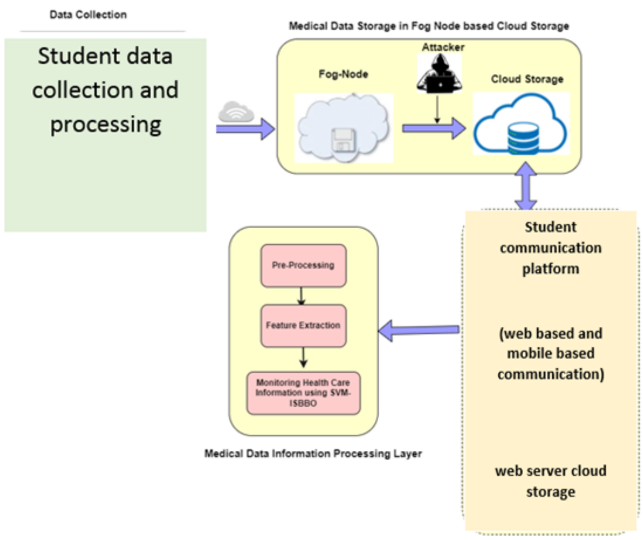

Fig. 3.1: Framework of SVM-ISPBO

3.2. Communication Data Storage in Fog-based Cloud Storage. The fog node lies between communication sensor devices and cloud storage computing. Sensor communication data were obtained from various wearable sensor devices. It minimizes latency, provides security, enhances the reliability of storing information, and has high storage capacity. Communication data were collected from all sensor devices and it has been transmitted to fog-node-based cloud storage. These communication data are transmitted for a pre-processing stage of the communication data information processing layer. In the monitoring of communication information, fog computing facilitates the processing of communication data without reducing its dimensionality of data and also prevents congestion of the network. Communication data stored in the cloud storage are transmitted to a communication server, the teachers monitor the health information and send the health status to the student via mobile application.

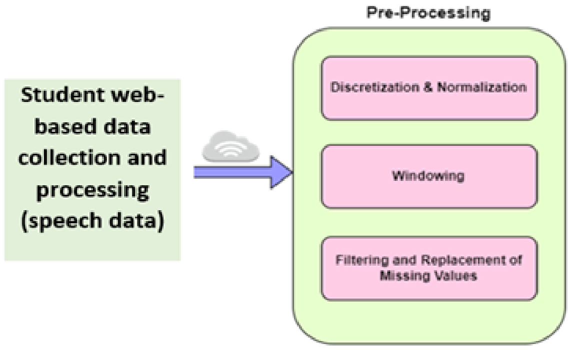

Fig. 3.2: Pre-Processing

3.3. Communication Data Information Processing Layer. The communication data information processing layer contains three modules namely pre-processing, feature extraction, and monitoring English communication information using SVM-ISPBO.

3.3.1. Pre-Processing. The communication sensor information is obtained from various sensor devices and it is in various formats like images, time series, numerical values, etc. And also, it may contain random samples as well as continuous sample structures. Therefore, pre-processing steps are needed for handling various formats of collected data. The steps involved in the pre-processing are given in Figure 3.2.

Discretization & Normalization. For the discretization of collected communication sensor data, the aspects of frequency and time are essential one. For that this paper uses standardized collected sensor values in the range between 0 and 1 is termed normalization. In order to handle the complex variations of sensor data and for the prediction of diseases based on the regression analysis and it can be evaluated as:

$$Q = \beta_0 + \beta_i M + \epsilon_i \text{ for } i = 1, 2, \ldots m \tag{3.1}$$

The sample input sensor communication data along with its variance and error value is termed by ϵ_i. The least square values are denoted by β_0 and β_i. The average values are evaluated from the sample input communication sensor data, by using standard deviation which is defined as:

$$\mu = \frac{\sum_{i=1}^{n} M_i}{Frequ} \tag{3.2}$$

Here, $Frequ$ represents the frequency of data and M_i is the sample communication input sensor data. Then the normalization is denoted by:

$$n_q = \frac{\in_i^*}{\sigma_i} \tag{3.3}$$

$$n_q = \frac{M_i - \mu_i}{\sigma_i} \tag{3.4}$$

Here $\in_i^*$ is residual value and σ_i is variance.

Windowing. The basic concept of windowing is splitting of communication sensor signal values into small segments in the aspect of time domain. Here the communication input sequence of senor signals is sen_1, sen_2 , ..., sen_n and it is separated into windows with equal number of sensor activities $acw_1, acw_2, \ldots, acw_n$. Here acw_1 is defined as window by signifying $[sen_i - \Delta sen, sen_i]$. The length of the window is varied from one window to another. Based on the time domain two sensor signal activities are fall into the same window.

3.3.2. Feature Extraction. In order to detect the attack in the storing of communication information feature extraction is an essential one. It extracts the significant features or relevant features from the dataset. In this work of SVM-ISPBO, which extracts the statistical features of mean, entropy, variance, and standard deviation.

Mean. It is the ratio of sum of communication data to the total number of communication data in the database. It is represented as:

$$mean=\frac{1}{y}\sum_{i=1}^{y}Q_i \tag{3.5}$$

Here y represents the total instances in the dataset and Q_i is the i^{th} data.

Entropy. Analysing the probability of arranging communication sensor data with n ways and it is defined as:

$$entropy=-\sum_{x=1}^{Q}p_x\log_2 p_x \tag{3.6}$$

Here, p_x is the probability of data and x is the possible sample data values.

Variance. It is the mean squared difference between every communication sensor data in the dataset and its mean value, which is represented by:

$$variance=\frac{1}{y-1}i\sum_{i=1}^{y}\left(Q_i-mean\right)^2 \tag{3.7}$$

Standard Deviation. It is defined as root of variance, which is represented as follows:

$$\sqrt{\frac{1}{y-1}i\sum_{i=1}^{y}\left(Q_i-mean\right)^2} \tag{3.8}$$

3.3.3. Monitoring MCPS based Communication information using SVM-ISBBO (Proposed). In the communication cyber physical system-based model monitoring the student information and storing the information securely in the fog node-based cloud storage system uses support vector machine with optimized algorithm of improved satin bower bird optimization algorithm (SVM-ISBBO). In this communication cyber physical system are integrates the various communication sensor devices and obtained the communication-based sensor information and stored in fog node-based cloud storage system in a secure manner.

3.3.4. Support Vector Machine in MCPS web communication monitoring. In the smart English communication cyber physical system, communication sensor signals are obtained from various communication sensor devices. After applying the pre-processing stage, extract the relevant features of the communication sensor information. SVM algorithm is used for analysis of collected communication sensor signals of the student. By using MCPS, SVM algorithm classifies the communication sensor information based on its range of value. MCPS monitored the communication sensor signal information and analysis that critical situation of student, immediately itsends the alert message to student's physician and caretaker.

The mathematical formulation of applying SVM is to find the optimal hyperplane which separates the features of the labelled data. Let $\mathcal{H}$ is the Hilbert space with inner product of $\langle .,. \rangle$ and its induced norm $\|.\|$. let us consider $\mathbb{R}^l$ be the m-dimensional Euclidean distance space and it is defined as $\emptyset : \mathbb{R}^l \rightarrow \mathcal{H}$ is a mapping function. For a training communication data set,

$$MTD_l=\left\{\left(p_i,\ q_i\right)|p_i\in\{-1,1\}\right\}_{i=1}^{l} \tag{3.9}$$

Here q_i is the label of p_i and its marginal function maf_l is defined as follows:

$$maf_l\left(p\right)=\langle\omega,\emptyset\left(p\right)\rangle+\theta,\ p\in\mathbb{R}^l \tag{3.10}$$

Here θ is the bias term, to yield optimal hyperplane ω and θ are used in training data set. Toi get the optimal hyperplane, objective function is required,

Minimize: $t(\omega,\theta) = \frac{1}{2}\|\omega\|^2 + Cp\sum_{i=1}^{k}\xi_i$

Subject to constraints: $q_i(\omega, \emptyset(a_i) + \theta) \geq 1 - \xi$

$$\xi \geq 0,\ i = 1, 2, \ldots, k$$

Here Cp is the regularization parameter and by using Lagrange multiplier method Equation 3.3.4 can be rewritten as follows to get optimal vector ω .

$$\omega = \sum_{i=1}^{l} \alpha_i q_i\ \emptyset(p_i)$$

Subject to constraints : $\sum_{i=1}^{l} \alpha_i q_i = 0$

Here α_i is $i = 1, 2, \ldots, l$. Substitute Equation 3.3.4 in Equation 3.9,

$$maf_l(p_0) = \langle \omega, \emptyset(p_0)\rangle + \theta$$

$$= \left\langle \sum_{i=1}^{l} \alpha_i q_i\ \emptyset(p_i), \emptyset(p_0) \right\rangle + \theta \tag{3.11}$$

$$= \sum_{i=1}^{l} \alpha_i q_i \langle \emptyset(p_i), \emptyset(p_0)\rangle + \theta$$

Let $L : \mathbb{R}^l \times \mathbb{R}^l \to \mathbb{R}$ be a kernel function and it can be expressed as follows:

$$L(p_i, p_j) = \langle \emptyset(p_i), \emptyset(p_j)\rangle \tag{3.12}$$

Then based on Equation 3.11

$$mtd_k(p_0) = \sum_{i=1}^{l} \alpha_i q_i L(p_i,\ p_0) + \theta \tag{3.13}$$

Now SVM can be represented as follows:

$$sv_l(p_0) = sgn(maf_l(p_0)) = \begin{cases} 1 & if\ maf_l(p_0) \geq 0 \\ -1 & if\ maf_l(p_0) < 0 \end{cases} \tag{3.14}$$

Here the support vectors are trained with training data set of non-zero value of α.The kernel function L and coefficient C, and it is used to classify the data. This SVM technique monitors the abnormal status of student health status and securely storing of communication information in fog node-based cloud storage platform. To improvising and more accurate monitoring of abnormal status of student health status based on the wearable sensor information optimization algorithm is required. Therefore, this work implements the improved satin bowerbird optimization algorithm.

3.3.5. Improved Satin Bower Bird Optimization Algorithm. Satin Bowerbird Optimizer (SBBO) is an is an intelligent optimization algorithm, determines that in the wild the adult male of Satin Bowerbird which simulates the breeding behavior. It has a strong power of survival and skill in reproduction. By constructing courtship cabin the matured Satin Bowerbird wins the female by attracting it by holding aluminous object in its beak, continuous loud singing which improves the probability of successful courtship. The male Satin Bowerbird constantly resists the challenges of its competitors and protect its nest from damage based on its survival rules. The steps involved in the SBO for the detection of attack in MCPS model and monitors the student information in an effectively.

Step 1. For initialize the population of Satin Bowerbirds randomly, this paper uses Logistic chaotic map for initialize the population of Satin Bowerbirds which improves the diversity of initial population, optimized accuracy and speed in convergence. Therefore, it is called as improved Satin Bowerbird optimization algorithm (ISBBO). This Logistic chaotic map is defined as:

$$P_{i+1} = \mu P_i * (1 - P_i) \tag{3.15}$$

The value of μ as a control parameter which ranges from 0 to 5. When the value of μ is larger as 5, then its initialization of population will get enhanced. In the solution space various courtship cabin is generated for various satin bowerbirdMB.

Step 2. Evaluate the fitness function of each individual satin bowerbird and compute the ratio of fitness function to overall fitness function value based on the probability of individual selection of satin bowerbird. This probability of selection of courtship cabin is computed by:

$$Proba_j = \frac{fit_j}{\sum_{m=1}^{MB} fit_m} \tag{3.16}$$

$$fitn_j = \begin{cases} \frac{1}{1+f(y_j)} \ , \ f\left(y_j\right) \ \geq 0 \\ 1 + \lceil \ f\left(y_j\right) \rceil \ , \ \ f\left(y_j\right) < 0 \end{cases} \tag{3.17}$$

The fitness value of $fitn_j$represents thatj^{th} courtship cabin and $f\left(y_j\right)$ is the objective function of j^{th} courtship cabin

Step 3. Update the position of male Satin Bowerbird optimization algorithm in the last iteration by using:

$$y_{jk}^{iter+1} = y_{jk}^{iter} + \lambda_k \left(\left(\frac{y_{lk} \ + y_{elite,k}}{2} \right) - y_{jk}^{k} \right) \tag{3.18}$$

Here y_{jk}^{iter} is the k-dimensional component of j^{th} individual male satin bowerbird in the $iter^{th}$ iteration. y_{lk} is the k-dimensional component of present global optimal position of population. The step factor of λ_k is evaluated by:

$$\lambda_k = \frac{\alpha}{1 + a_j} \tag{3.19}$$

Here α is the maximum step size and a_j is the probability of choosing the target courtship cabin with value [0,1]. From the Equation 3.19 clearly shows that for the selection of target location with respect to greater probability along with its smaller step size. If the probability of selection of target location is 0 means, then its step size is largest and it is represented as α. Similarly, If the probability of selection of target location is 1 means, then its step size is largest and it is represented as $\alpha/2$.

Step 4. To prevent local optimization, strong male satin bowerbird often steals from other male satin bowerbird courtship cabins and destroys the cabins. At the end of each iteration of ISBBO algorithm, randomly improve the mutation process. At this stage, y_{jk} follows the normal distribution and it is represented as:

$$y_{jk}^{iter+1} \ \sim M\left(y_{jk}^{iter}, \ \sigma^2\right) \tag{3.20}$$

$$M\left(y_{jk}^{iter}, \ \sigma^2\right) = y_{jk}^{iter} + \left(\sigma * M\left(0,1\right)\right) \tag{3.21}$$

The evaluation of standard deviation is:

$$\sigma = z * \left(vari_{max} - vari_{min}\right) \tag{3.22}$$

Here, scaling factor is denoted by z and $vari_{max}$, $vari_{min}$ are upper limit and lower limit of variable y_i.

Table 4.1: Description of features in the Cleveland dataset

Features	**Description**
p.Age	Age of student in years
p.Sex	Female or Male
p.Chole	Measure of serum cholesterol
p.Chp	Types of chest pain
T_restbps	Resting blood pressure
F_bs	fasting blood sugar
Rest_ecg	Resting measure of electrocardiographic
Thalach	maximum heart rate
Exang	Exercise caused angina
Oldpeak_ ST	ST depression caused by exerciserelative to rest
Slope	Slope of the peak exercise ST segment
Ca	Number of major vessels of coloured by Flourosopy
Thal	Type of Defect

Step 5. Based on initial population and population generated from mutation process in each iteration new population is formed. The fitness value function is generated for all individual male satin bower bird with its combination of population. This generated population is arranged in ascending order. In the analysis of individual male satin bowerbird has minimum fitness function value are removed. It retained only the largest fitness function value of male satin bowerbird. In this stage the optimal solution is computed and repeat the process until it reaches the maximum iteration. This SVM-ISBBO algorithm improvising and produce more accurate monitoring of abnormal status of student health status based on the wearable sensor information and send alert message to the student through physician in proper time. The student information also securely stored in the fog node based cloud storage platform.

4. Result & Discussion. The proposed work of SVM-ISBBO is used for monitoring the health information and securely storing the communication information. This proposed work SVM-ISBBO is evaluated the performance of analysis in the aspect of detection of accuracy, prediction of attack, ratio of delay, cost of communication, sensitivity, specificity and F1-Score.

4.1. Data Set Description. The dataset used in an effective communication cyber physical system for monitoring and securely storing communication information using fog computing service is Cleveland dataset from the UCI repository.The attributes are collected from various communication sensor devices like temperature sensor, ECG, pulse oximeter, temperature, and blood pressure sensors. The data were collected and saved in the fog node-based cloud storage platform. It consists of 5060 records, 13 features. Table 4.1 is the description of Cleveland dataset. This dataset contains heart disease related information.

This proposed work is compared with existing algorithms of KNN [22], NB, SVM[5].

True Positive Rate (TPR). The attack in the MCPS is exactly classified as an attack is known as sensitivity.

$$TPR=\frac{TP}{TP+FN} \tag{4.1}$$

False Positive Rate (FPR) or Miss Rate. It is also called as false alarm. This identified the normal data is considered as an incorrectly identified as an attack.

$$FPR=\frac{FP}{FP+TN} \tag{4.2}$$

False Negative Rate (FNR) or Fall Out. It is also called as miss rate. Incorrectly identified the attack data. that is, true positive will be missed.

$$FNR=\frac{FN}{FN+TP} \tag{4.3}$$

Table 4.2: performance metric measures of SVM-ISBBO

Algorithm	**TPR**	**TNR**	**Miss Rate**	**Fall Out**	**MCC**
KNN	0.793	0.764	0.078	0.061	0.25
NB	0.789	0.752	0.082	0.064	0.36
SVM	0.863	0.834	0.087	0.59	0.21
SVM-IBBO(Proposed)	0.931	0.911	0.059	0.051	0.18

True Negative Rate (TNR). The normal data is correctly predicted as normal and it is called as specificity.

$$TNR=\frac{TN}{TN+FP} \tag{4.4}$$

Mathews Correlation Coefficient (MCC). It is a corelation between predicted output with real data.

$$MCC=\frac{(TP.TN)-(FP.FN)}{\sqrt{(TP+FP).\,(TP+FN)\,.\,(TN+FP)\,.(TN+FN)}} \tag{4.5}$$

MSE. The mean squared error (MSE) calculate the average of the squares of the differencesbetween the predicted values and actual values.

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(y_{pi}-y_{ai})^2 \tag{4.6}$$

RMSE. It is similar to MSE but for compute this by root of MSE.

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{pi}-y_{ai})^2} \tag{4.7}$$

From the table 4.2, the proposed SVM-IBBO in the monitoring of health information using MCPSis given. The proposed work of SVM-IBBO got 0.931 in TPR, 0.911 in TNR, 0.059 for miss rate , 0.051 in fall out and MCC 0.18.

Percentage Rate of Delivery Communication Sensor Data Packet. The percentage of delivery of communication sensor information is determined by number of packets of communication information delivered for a particular time in an effective way. The percentage between the sent packet of communication sensor data and obtained packet of communication sensor data is evaluated as delivery percentage rate of communication sensor data packets. This can be shown in Figure 4.1.

From the Figure 4.1 it seems that the number of sensor devices increases and transmitting rate of communication sensor values are decreased in the proposed work of SVM-IBBO. Therefore, it produces high delivery percentage rate of communication sensor data packets.

Response Rate. When transmission of communication sensor information from various sensor devices to fog node-based cloud storage platform. Response rate is rate of interaction of sensor devices for obtained the sensor information and stored it in fog node. This period of response in the network is given in Figure 4.2.

From the Figure 4.2 seems that the proposed work SVM-IBBO gives high response rate of transmission of communication sensor information. Figure 4.3 shows that error rate in the monitoring of English communication sensor information.

In the analysis of monitoring of health-based sensor information our proposed work SVM-ISBBO requires minimum error rate. Figure 4.4 shows that accuracy rate of proposed work.

In the analysis of Figure 4.4, shows that accuracy rate of KNN got 78.56% , NB got 81.74%, SVM got 85.15% and proposed work of SVM-ISBBO got 92.34%.

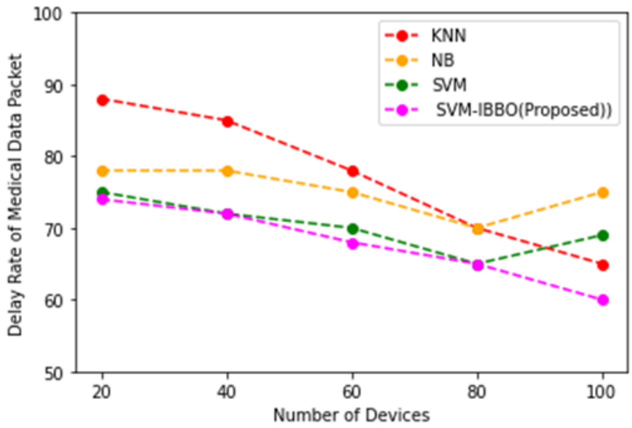

Fig. 4.1: Percentage Rate of Delivery Communication Sensor Data Packet

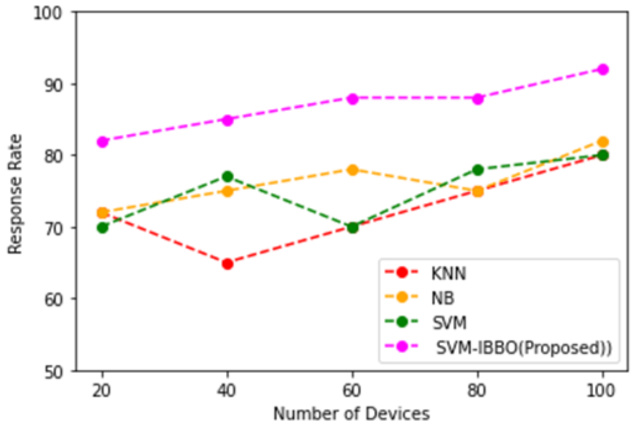

Fig. 4.2: Response Rate

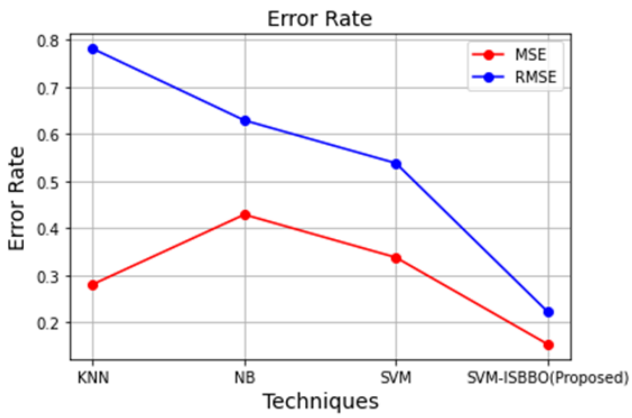

Fig. 4.3: Error Rate

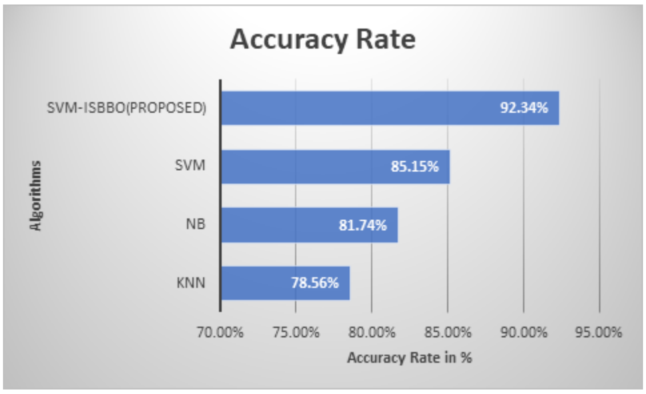

Fig. 4.4: Accuracy Rate

5. Conclusion. An effective communication cyber physical system for monitoring and securely storing communication information using fog computing service using SVM-ISBBO was implemented. Communication sensor information is obtained from various wearable sensor devices of student's body and storing this information securely in fog node computing until it safely transmitted to communication server for permit the teachers to access it. In this work Cleveland dataset is used. This proposed work SVM-ISPBO monitors the students' heart rate, temperature, blood pressure etc and these values are obtained from wearable sensor devices and its notifications are sent back to teachers. Teachers' diagnosis the student information and sent back the alert notifications to the students for taking proper medications. The accuracy rate of KNN got 78.56% , NB got 81.74%, SVM got 85.15% and proposed work of SVM-ISBBO got 92.34%.This proposed work produces high performance in various aspects of accuracy, TPR, TNR, Miss rate, fall out and monitor the abnormal communication sensor information in an efficient and accurately. In future, this work may be extended up to for providing more secure in the fog node by applying the encryption of communication sensor data.

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