Clustered IoT Based Data Fusion model for Smart Healthcare Systems

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Abstract

Futuristic sustainable computing solutions in e-healthcare applications were depends on the Internet of Things (IoT) and cloud computing (CC), has provided several features and realistic services. IoT-related medical devices gather the necessary data like recurrent transmissions in health limitations and upgrade the exactness of health limitations all inside a standard period. These data can be generated from different types of sensors in different formats. As a result, the data fusion is a big challenge to handle these IoT-based data. Moreover, IoT gadgets and medical parameters based on sensor readings are deployed for detecting diseases at the correct time beforehand attaining the rigorous state. Machine learning (ML) methods play a very significant task in determining decisions and managing a large volume of data. This manuscript offers a new Hyperparameter Tuned Deep learning Enabled Clustered IoT Based Smart Healthcare System (HPTDLEC-SHS) model. The presented HPTDLEC-SHS technique mainly focuses on the clustering of IoT devices using weighted clustering scheme and enables disease diagnosis process. At the beginning level, the HPTDLEC-SHS technique exploits min-max data normalization technique to convert the input data into compatible format. Besides, the gated recurrent unit (GRU) model is utilized to carry out the classification process. Finally, Jaya optimization algorithm (JOA) is exploited to fine tune the hyperparameters related to the GRU model. To demonstrate the enhanced performance of the HPTDLEC-SHS technique, an extensive comparative outcome highlighted its supremacy over other models.

Keywords: Data Fusion; Internet of Things; Healthcare system; Deep learning; Clustering; Jaya optimization algorithm

1. Introduction

The ongoing development of Information and Communication Technologies (ICT) and installed systems addresses the presentation of an original innovation: Internet of Things (IoT). It permits articles and people in virtual conditions and the actual world to interrelate with each other [1,2]. An impressive number of machines conveying IoT as a significant information assortment component, structure smarter conditions like smart urban communities, homes, medical services, and smart transportation [3]. The blend of IoT and cloud-situated web-based machines perform better compared to regular cloud-arranged apparatuses for adequacy [4-6]. The rising number of machines in businesses, for example, banking, military, and the clinical field can utilize this mixture. Especially, the cloud-situated IoT assists offer proficient services to wellbeing with really focusing machines on getting to and observing records from far off areas. The medical services industry has shown significant development lately, contributing fundamentally to income and business. However, the data fusion is the big challenge is these systems. In the beyond couple of years, the determination of illnesses and irregularities in the human body was conceivable solely after having an actual assessment in the clinic. A large portion of the patients stayed in the clinic all through their treatment cycle, which brought about higher medical care expenses and burden on provincial and distant wellbeing offices. Through the innovative progressions accomplished over the long haul, it is currently workable for scaled down

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gadgets, for example, smartwatches to analyze different sicknesses and screen their wellbeing. IoT-based clinical machines gather the necessary information, for example, repetitive changes in wellbeing limitations, and update the meticulousness of wellbeing requirements generally inside a standardized period [7]. Likewise, IoT gadgets and clinical boundaries connected with sensor readings will be conveyed for distinguishing infections inside the right time prior to arriving at the thorough state. Machine learning plans are playing the main errand in simply deciding and handling a bigger amount of information [8]. The technique of adjusting information investigation plans to the unmistakable regions includes characterizing information types, for example, volume, assortment, and speed.

IoT is a steadily developing innovation that can utilize dispersed figuring and the capacity to trade information to settle on fast choices for system needs inside a tremendous conveyed network. This innovation interfaces ordinary articles (smartphones, smart watches, smart lights, and so on) like sensors, actuators, and things to the Internet by means of existing organizations to work with the determination and follow-up of patients while expanding the productive utilization of emergency clinic assets [9]. IoT applications are created to utilize this associated network, depending on a computerized climate. This offers new chances to give quick and exact reactions by getting pertinent information. This wise organization can get information from a few sources, process information locally utilizing the diminished registering power, and/or in a unified way with higher computerized figuring assets to settle on smarter choices. From this, shrewd suggestions, prescient examination, or example identification can be made.

With these shrewd capacities, IoT innovation likewise empowers the improvement of Quality of Service (QoS). The information trade is furnished with a ceaseless stream between patients, specialists, drug and biomedical providers, and so forth. In this sense, IoT utilizes progressed IT innovation to coordinate the different parts of a cooperative organization to work on the proficiency, service capacity, and adaptability between smart gadgets. However, a data preparation model is needed to handle the different formats of data, or what we call a data fusion. These smart gadgets can screen and detect their natural circumstances, and measure the exercises or the capacities in the introduced stages. The accumulated information then, at that point, can be passed on to an administration unit/decision support system for additional handling. Gathered tactile information can be utilized to understand what is happening by observing the conditions of every unit in the organization and the situation with the total system. As an initial step, information handling technologies can likewise be utilized to change crude into input information. Handled input information can be changed over into significant information utilizing information handling procedures and at long last, this information can empower the system to give self-activity through information handling approaches without human contribution. All in all, IoT systems can make independent systems by means of self-administration and self-administration capacities [10].

Deep learning is another arising region that has achieved huge outcomes in blended methodology information settings, succession forecast, and regular language handling undertakings that have acquired development in a few applications like discourse acknowledgment, PC vision, and so forth [11]. Furthermore, group learning is used to obtain the unrivaled consequences of a few machine learning calculations. One of the effective group approaches is the "bag classifier," which is prepared by fitting the assessor on random subgroups of information and, further, their singular recognizable pieces of proof are amassed through averaging or casting a ballot to come by the last anticipated results. These assessors help with lessening the difference more effectively than a solitary assessor through randomizing the information. High level deep learning approaches have achieved a high exactness rate for expectation and order of medical care information.

This manuscript offers a new Hyperparameter Tuned Deep learning Enabled Clustered IoT Based Smart Healthcare System (HPTDLEC-SHS) model. The presented HPTDLEC-SHS technique mainly focuses on the clustering of IoT devices using weighted clustering scheme and enables disease diagnosis process. At the beginning level, the HPTDLEC-SHS technique exploits min-max data normalization technique to convert the input data into compatible format. Besides, the gated recurrent unit (GRU) model is utilized to carry out the classification process. Finally, Jaya optimization algorithm (JOA) is exploited to fine tune the hyperparameters related to the GRU model. To demonstrate the enhanced performance of the HPTDLEC-SHS technique, an extensive comparative outcome highlighted its supremacy over other models.

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2. Related Works

Nagarajan et al. [11] suggest remote health monitoring and data analysis by compiling IoT and DL ideas. The new IoT related FoG assisted cloud network architecture was suggested that collects real-time medical data from patients through numerous health care IoT sensor networks, such data were examined with the help of DL technique positioned at Fog related Healthcare Platform. In [12], Ambient Intelligence aided Health Monitoring System (AmIHMS) having IoT gadgets was suggested for student health observation. WSNs were leveraged to collect the data needed by Ami atmospheres. The cloud would manage the surged volume of health data, interchange data in effective ways in medical networks, and make Big Data Analytics sustainable. Abou-Nassar et al. [13] suggest a Blockchain Decentralised Interoperable Trust structure (DIT) for IoT areas where a smart contract guarantees validation of budgets and Indirect Trust Inference System (ITIS) minimizes semantic gap and improvises trustworthy factor (TF) valuation through the network edges and nodes. This DIT IoHT uses private Blockchain ripple chain for establishing trustworthy transmission by authenticating nodes depends on it inter operable framework so measured transmission needed for solving fusion and integrating problems were eased via distinct areas of the IoHT structure.

Elayan et al. [14] suggest and apply an intellectual context-aware healthcare system by making use of the DT structure. This structure was beneficial input to digital health care and for improvising health care functions. An ECG heart rhythms classifier method has been constructed by making use of ML for diagnosing heart disease and identifying heart issues. The applied methods effectively forecasted a specific heart condition having high accuracy in distinct algorithms. In [15], a sustainable lung cancer detection method was advanced for integrating computational intelligence and the Internet of Health Things (IoHT), making minimal damage to the atmosphere. IoHT unit maintains connectivity endlessly produces data from patients. Heuristic Greedy Best First Search (GBFS) technique was utilized for selecting most related features of lung cancer data upon that RF method was implied for classifying and distinguishes lung cancer affected patients from normal ones depends on noticed indications. In [16], a medical monitoring scheme for cloud-based IoT platform was suggested, in which the medical conditions of patients were extracted via forecasting illnesses by mining her biological data gathered from IoT gadgets and other medical reports. A disease diagnosis method was utilized for analyzing the medical data of patients for the focus of providing composite health or medical prescription.

3. The Proposed Model

In this study, a new HPTDLEC-SHS model has been developed for clustering IoT devices using weighted clustering scheme and enables disease diagnosis process. The system architecture is shown in Fig. 1. At the beginning level, the HPTDLEC-SHS technique exploits min-max data normalization technique to convert the input data into compatible format. Besides, the GRU model is utilized to carry out the classification process. Finally, JOA has exploited to fine tune the hyperparameters related to the GRU model.

3.1 Min-Max Normalization

At the beginning level, the HPTDLEC-SHS technique exploits min-max data normalization technique to convert the input data into compatible format. Data normalization of mathematical kind is significant in other datasets. Simultaneously, for each record in the dataset, the range of values varies as the value of the feature is dissimilar under each aspect. The normalization task makes the record feature attribute into relative value, thus improving the classification accuracy and convergence rate. Two widely available normalization techniques are Min-Max normalization technique and the Z-score normalization approach. The min-max method is applied, given that the outcomes of the linear conversion process of the real dataset lie within the interval of zero and one as follows:

$$x_{scale} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In Eq. (2), x indicates a current value, x_{min} and x_{max} denotes the minimum and maximal values of the attribute and x_{scale} indicates the measure along the attribute matching procedure.

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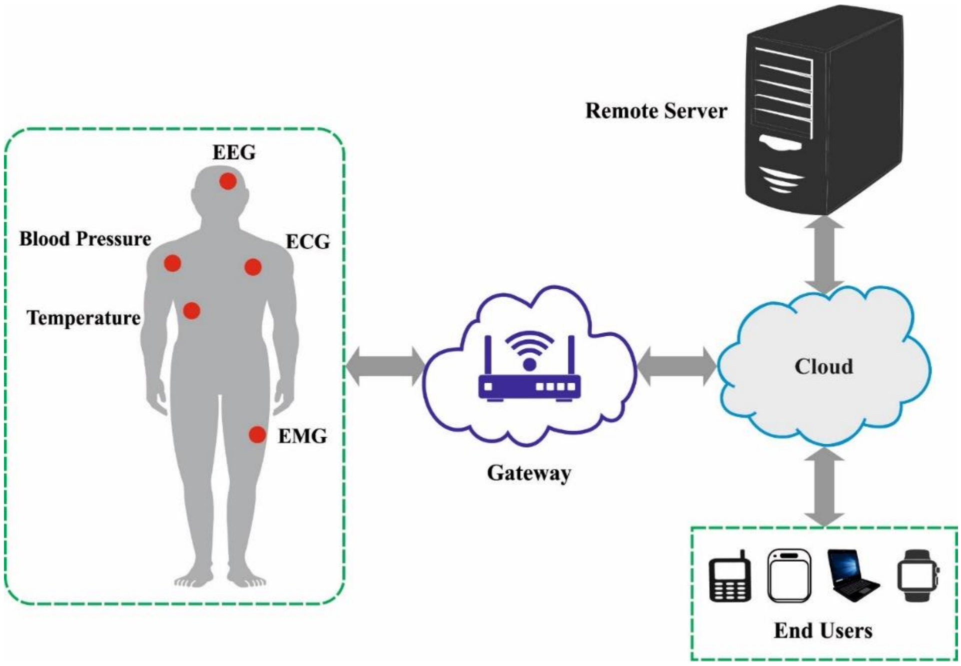

Figure1: System architecture

3.2 GRU based Classification

Here, the GRU model is utilized to carry out the classification process. GRU is presented by Cho et al. to generate all the recurrent units for adaptably capturing the dependency of various time scales. The GRU contains 2 gates, reset gate r and update gate z. Intuitively the reset gate defines that for combining a novel input data with preceding memory, and update gate demonstrates the count of preceding memory stored to present time step.

It can utilize the preceding state $h_{(t-1)}$ and the current input x_t for obtaining the recent reset gate r_t and update gate z_t.

$$r_t = \sigma(W_r \cdot [h_{t-1'} x_t]) \tag{2}$$

$$z_t = \sigma(W_z \cdot [h_{t-1'} x_t]) \tag{3}$$

The reset gate must reset the preceding state h_t to h_{t-1} and concatenate $\tilde{h}_{t-1}$ with x_t. Afterward, a $tanh$ function was utilized for zooming the data to range of -1 and 1.

$$\tilde{h}_t = tanh(W_{\tilde{h}} \cdot [r_t * h_{t-1}, x]) \tag{4}$$

The $\tilde{h}_t$ contains the current input data x_t and it can be pertinent to current hidden state as it memorized the current state. Afterward, it can utilize the update gate for updating the state. The upgrade is concurrently forget and choose the memory

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t \tag{5}$$

The resultant layer utilizes a sigmoid function.

$$y_t = sigmoid(W_0 \cdot h_t + b_y) \tag{6}$$

In Eqs. (4)-(8) from the forward propagation procedure, it is obvious that parameters selected learned are W_r, W_z, $W_{\tilde{h}}$, and W_0. $W_{...}$ are weighted matrices that are upgraded from the process of backward pass.

The trained GRU is related to typical NN, utilizing BP technique, however, there are some variances. While the parameter of GRUs was generally utilized by every time step, the gradient of all the input doesn't only dependent upon the computation of present steps. It can be called BP, Through Time (BPTT). The fundamental and simplified formula of GRU is

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$$s_t = f(Ux_t + iVs_{t-1}) \tag{7}$$

$$\hat{y}_t = softmax(V_{s_t}) \tag{8}$$

The cross entropy (CE) loss was determined as:

$$E_t(y_t, \hat{y}_t) = -y_t \log y_t \tag{9}$$

$$E(y, \hat{y}) = \sum_t E_t(y_t, \hat{y}_t) = -\sum_t y_t \log\hat{y}_t \tag{10}$$

whereas $\hat{y}_t$ refers the right answer and y_t signifies the forecast. Giving the entire sentence as the trained sample, an entire error is the sum of errors from all the times t. The purpose is for calculating the error gradient initial, afterward utilizing the GD technique for learning parameters. It can accumulate errors, it also accumulates the gradient at all the time points, i.e.,

$$\frac{\partial E}{\partial W} = \sum_t \frac{\partial E_t}{\partial W} \tag{11}$$

Afterward computing the partial derivatives to all the parameters W, the parameter W is upgraded and iterated from order still the loss converges.

During this figure, $\frac{\partial s_1}{\partial s_0}, \frac{\partial s_2}{\partial s_1}, \frac{\partial s_3}{\partial s_2}, \frac{\partial E_3}{\partial s_3}$ denotes the gradients that pass through time. All the circles S_j implies the resultant value to time i and an input value for time $i+1$ from the hidden layer. E_j denotes the CE error and x_i defines the instance data of input layers.

3.3 JOA based Hyperparameter Tuning

At the last stage, JOA has exploited to fine tune the hyperparameters related to the GRU model. A word "Jaya" denotes accomplishment and hence, JOA repeatedly hunts towards the achievement that is for extracting an optimum outcome from the available one. A significant feature of the JOA is that it implements the revealed optimization process by using common control parameters and is not reliant on certain parameters. The exclusive abilities of JOA ensure quick convergence features, minimal employment complexity when compared to other conventional optimization techniques, and reduced computation time. It is notable, to some offline optimization approaches; the quality of solution is given major concern as interrelated the convergence rate. With that regard, a JOA is verified and found optimum in contrast to the known optimization evolutionary methods for example PSO, grenade explosion method (GEM), DE, genetic algorithm (GA), teaching-learning based optimization (TLBO), and so forth

To accurately demonstrate the optimization technique of JOA, the subsequent representation is exploited. C indicates the decision number and R represents the complete amount of result candidates to an individual solution agent. x_{best}^{k} denotes an optimum among every candidate result to an arbitrary k^{th} iterations. On the other hand, x_{wrost}^{k} represents the worst of every candidate resulting to k^{th} iterations. Similarly, $x_{i,j}^{k}$ indicates the j^{th} decision to the arbitrary i^{th} candidate for k^{th} iterations. Eq. (9) indicates the mathematically modeled technique to the desirable outcomes in k^{th} iterations.

$$X_{i,j}^{k} = x_{i,j}^{k} + \mu_{1,j}^{k}\left(x_{j,best}^{k} - \left|x_{i,j}^{k}\right|\right) - \mu_{2,j}^{k}\left(x_{j,wrost}^{k} - \left|x_{i,j}^{k}\right|\right). \tag{12}$$

Where, $\mu_{1,j}^{k}$ and $\mu_{2,j}^{k}$ indicates arbitrary number within zero and one in k^{th} iterations. $X_{i,j}^{k}$ is subject to the application of $x_{i,j}^{k}$ as an objective function. Therefore, iteration enhancement is implemented to consecutively improve the optimization issue. A technique consecutively improves itself until the desirable optimization is attained.

4. Results and Discussion

In this section, the experimental validation of the HPTDLEC-SHS model is carried out using medical data. Table 1 and Fig. 2 highlight the $sens_y$ inspection of the HPTDLEC-SHS model with other models. The outcomes implied the enhancements of the HPTDLEC-SHS model under all instances. For instance, with 2000 instances, the HPTDLEC-SHS model has offered increased $sens_y$ of 95.88% whereas the GNB, SVM, ID3, and ANN models have obtained reduced $sens_y$ of 90.47%, 93.65%,

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93.15%, and 90.81% respectively. Moreover, with 6000 instances, the HPTDLEC-SHS model has offered increased $sens_y$ of 96.23% whereas the GNB, SVM, ID3, and ANN models have obtained reduced $sens_y$ of 92.68%, 91.56%, 90.43%, and 91.74% respectively.

Table 1: $Sens_y$ examination of HPTDLEC-SHS with recent models

Sensitivity (%)					
No. of Instances	**GNB Model**	**SVM Model**	**ID3 Model**	**ANN Model**	**HPTDLEC-SHS**
2000	90.47	93.65	93.15	90.81	95.88
4000	92.81	90.23	91.48	90.40	95.75
6000	92.68	91.56	90.43	91.74	96.23
8000	93.28	90.15	92.44	90.25	95.70
10000	91.73	92.80	90.34	93.26	95.06

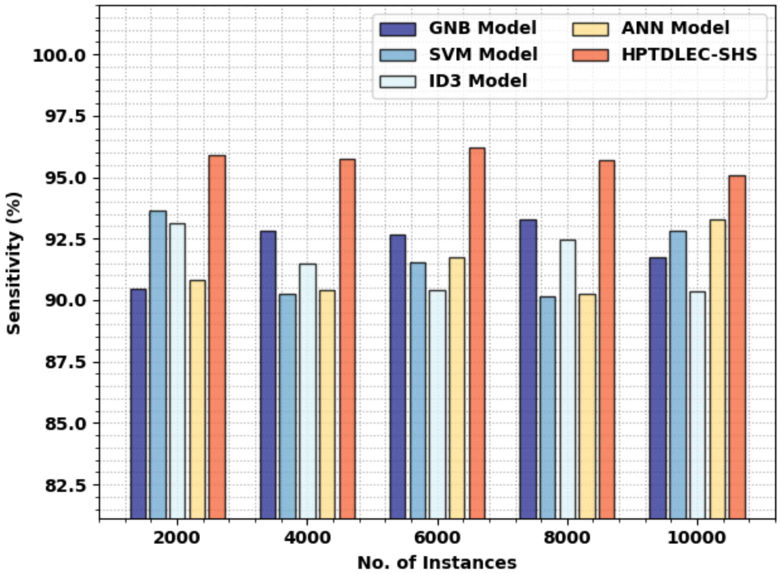

Figure 2: Comparative $sens_y$ examination of HPTDLEC-SHS with recent models

Table 2: $Spec_y$ examination of HPTDLEC-SHS with recent models

Specificity (%)					
No. of Instances	**GNB Model**	**SVM Model**	**ID3 Model**	**ANN Model**	**HPTDLEC-SHS**
2000	90.91	91.23	92.71	90.27	94.70
4000	91.23	91.43	90.94	93.23	96.28
6000	92.64	93.70	90.03	93.87	96.72
8000	92.10	93.20	92.62	90.32	95.97
10000	90.08	92.50	90.69	91.16	95.88

Table 2 and Fig. 3 highlight the $spec_y$ review of the HPTDLEC-SHS model with other models. The outcomes implied the enhancements of the HPTDLEC-SHS method under all instances. For instance, with 2000 instances, the HPTDLEC-SHS model has presented increased $spec_y$ of 94.70% whereas the GNB, SVM, ID3, and ANN models have gained reduced $spec_y$ of 90.91%, 91.23%, 92.71%, and 90.27% correspondingly. Also, with 6000 instances, the HPTDLEC-SHS model has provided increased $spec_y$ of 96.72% whereas the GNB, SVM, ID3, and ANN models have gained reduced $spec_y$ of 92.64%, 93.70%, 90.03%, and 93.87% correspondingly.

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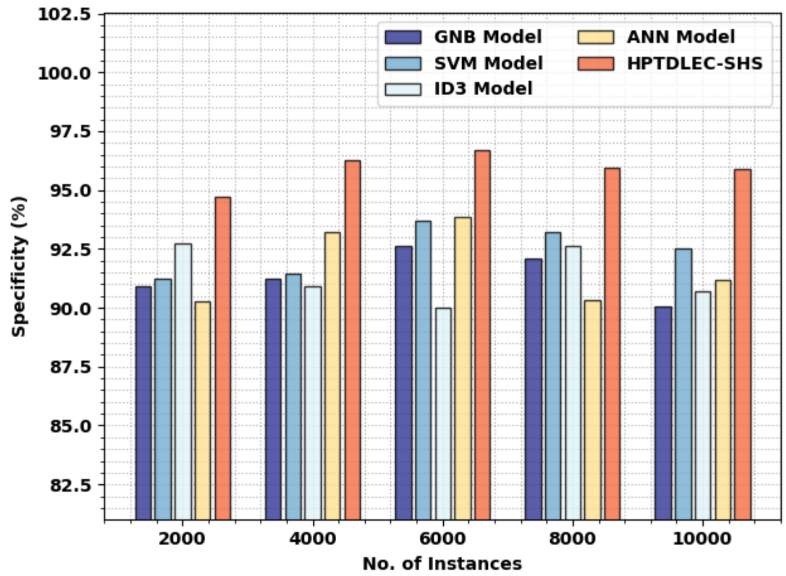

Figure 3: Comparative $spec_y$ examination of HPTDLEC-SHS with recent models

Table 3 and Fig. 4 highlight the $accu_y$ inspection of the HPTDLEC-SHS model with other models. The outcomes implied the enhancements of the HPTDLEC-SHS technique under all instances. For example, with 2000 instances, the HPTDLEC-SHS technique has offered increased $accu_y$ of 95.00% whereas the GNB, SVM, ID3, and ANN models have obtained reduced $accu_y$ of 93.34%, 91.84%, 90.55%, and 90.81% correspondingly. Besides, with 6000 instances, the HPTDLEC-SHS model has offered increased $accu_y$ of 95.27% whereas the GNB, SVM, ID3, and ANN models have gained reduced $accu_y$ of 90.21%, 92.52%, 90.66%, and 90.34% correspondingly.

Table 4 and Fig. 5 highlight the F_{score} examination of the HPTDLEC-SHS model with other models. The outcomes implied the enhancements of the HPTDLEC-SHS model under all instances. For instance, with 2000 instances, the HPTDLEC-SHS approach has rendered increased F_{score} of 95.75% whereas the GNB, SVM, ID3, and ANN models have gained reduced F_{score} of 93.10%, 91.49%, 90.13%, and 90.37% correspondingly. Also, with 6000 instances, the HPTDLEC-SHS approach has offered increased F_{score} of 96.64% whereas the GNB, SVM, ID3, and ANN models have reached reduced F_{score} of 93.74%, 93.81%, 93.62%, and 93.77% correspondingly.

Table 3: $Accu_y$ examination of HPTDLEC-SHS with recent models

Accuracy (%)					
No. of Instances	**GNB Model**	**SVM Model**	**ID3 Model**	**ANN Model**	**HPTDLEC-SHS**
2000	93.34	91.84	90.55	90.75	95.00
4000	92.14	90.90	91.22	93.37	96.68
6000	90.21	92.52	90.66	90.34	95.27
8000	93.13	90.60	91.04	92.01	95.33
10000	91.92	92.79	93.94	92.98	96.52

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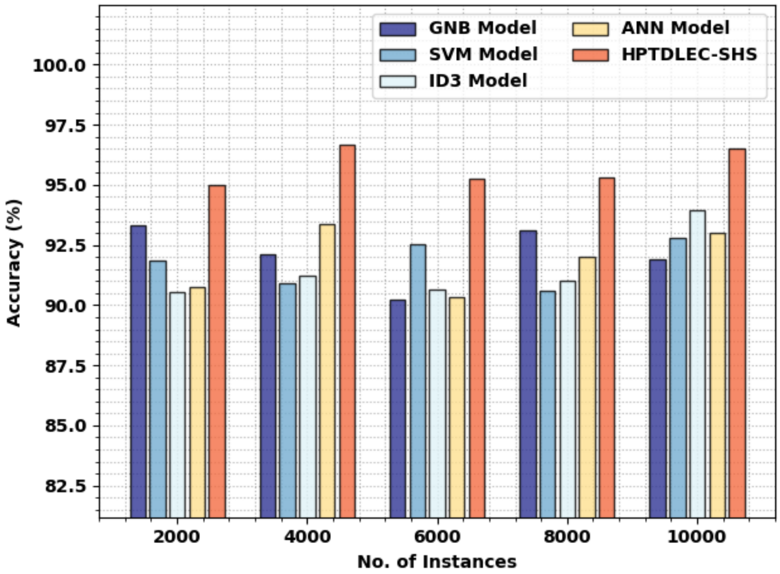

Figure 4: Comparative $accu_y$ examination of HPTDLEC-SHS with recent models

Table 4: F_{score} examination of HPTDLEC-SHS with recent models

F-Score (%)					
No. of Instances	GNB Model	SVM Model	ID3 Model	ANN Model	HPTDLEC-SHS
2000	93.10	91.49	90.13	90.37	95.75
4000	92.13	93.74	93.73	90.28	94.75
6000	93.74	93.81	93.62	93.77	96.64
8000	90.06	92.25	93.20	93.35	95.28
10000	91.73	92.93	91.00	91.31	96.75

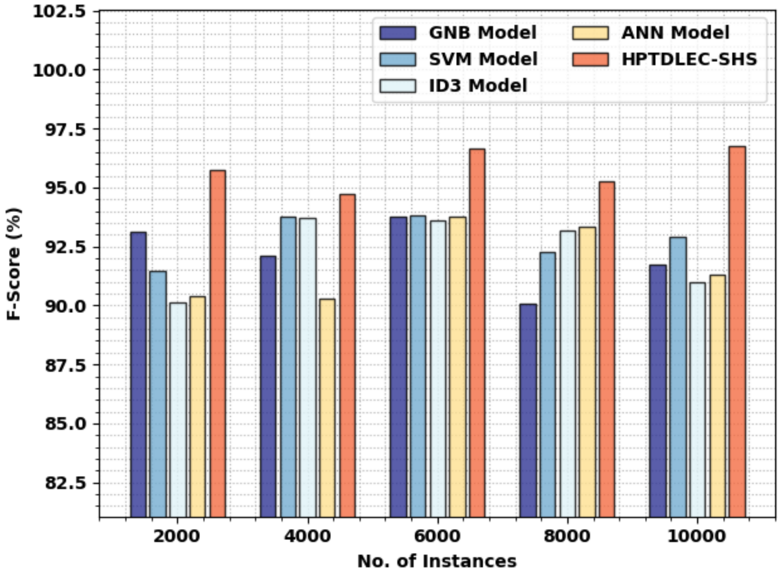

Figure 5: Comparative F_{score} examination of HPTDLEC-SHS with recent models

Table 5 and Fig. 6 highlight the MCC inspection of the HPTDLEC-SHS model with other models. The outcomes implied the enhancements of the HPTDLEC-SHS method under all instances. For instance,

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with 2000 instances, the HPTDLEC-SHS model has offered increased MCC of 94.75% whereas the GNB, SVM, ID3, and ANN algorithms have obtained reduced MCC of 90.29%, 91.42%, 93.02%, and 90.64% correspondingly. Furthermore, with 6000 instances, the HPTDLEC-SHS approach has provided increased MCC of 95.90% whereas the GNB, SVM, ID3, and ANN models have reached reduced MCC of 90.61%, 90.31%, 91.60%, and 91.69% correspondingly.

Table 5: MCC examination of HPTDLEC-SHS with recent models

MCC (%)					
No. of Instances	**GNB Model**	**SVM Model**	**ID3 Model**	**ANN Model**	**HPTDLEC-SHS**
2000	90.29	91.42	93.02	90.64	94.75
4000	93.26	92.11	93.34	90.91	95.01
6000	90.61	90.31	91.60	91.69	95.90
8000	91.73	91.16	93.47	91.69	95.96
10000	90.61	91.03	90.95	91.00	95.77

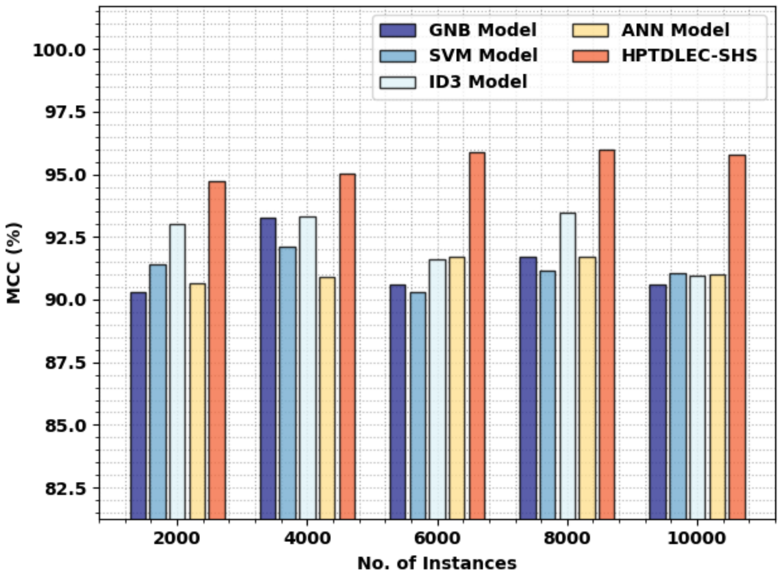

Figure 6: Comparative MCC examination of HPTDLEC-SHS with recent models

5. Conclusion

In this study, a new HPTDLEC-SHS model has been developed for clustering IoT devices using weighted clustering scheme and enables disease diagnosis process. At the beginning level, the HPTDLEC-SHS technique exploits min-max data normalization technique to convert the input data into compatible format. Besides, the GRU model is utilized to carry out the classification process. Finally, JOA has exploited to fine tune the hyperparameters related to the GRU model. To demonstrate the enhanced performance of the HPTDLEC-SHS technique, an extensive comparative outcome highlighted its supremacy over other models. Therefore, the HPTDLEC-SHS technique can be utilized for disease classification process in the IoT environment.

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