Multi-sensor Data Fusion based Medical Data Classification Model using Gorilla Troops Optimization with Deep Learning

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Abstract

Wireless Body Sensor Network (BSN) comprises wearables with different sensing, processing, storing, and broadcast abilities. Once several devices acquire the data, multi-sensor fusion was needed for transforming erroneous sensor information into maximum quality fused data. Deep learning (DL) approaches are utilized in different application domains comprising e-health for applications like activity detection, and disease forecast. In recent times, it can be demonstrated that the accuracy of classification techniques is enhanced by the combination of feature selection (FS) approaches. This article develops a Multi-sensor Data Fusion based Medical Data Classification Model using Gorilla Troops Optimization with Deep Learning (MDFMDC-GTODL) algorithm. The proposed MDFMDC-GTODL method enables collection of various daily activity data using different sensors, which are then fused to produce high-quality activity data. In addition, the MDFMDC-GTODL technique applies optimal attention based bidirectional long short term memory (ABLSTM) for heart disease prediction. In this study, Gorilla Troops Optimization Algorithm based FS (GTOA-FS) technique is involved to improve the classification performance. The simulation outcome of the MDFMDC-GTODL technique are validated and the results are investigated in different prospects. A wide-ranging simulation analysis stated the better performance of the MDFMDC-GTODL method over other compared approaches.

Keywords: Sensor applications; Medical data; Data fusion; Deep learning; Feature selection

1. Introduction:

The rapid development in sensing technology has enabled the healthcare industry to enhance the quality of its services. Moreover, the model of small and lightweight smart sensors has empowered systems to perform a vital part of progressive developments in unobtrusive and unsupervised methods for home-rehabilitation and the continuous observation of patients' health conditions [1]. Currently, wireless tracking of human body parameters has allured crucially because of its extensive applications namely surveillance, rehabilitation, sport science, medical science, and virtual reality. The wireless sensor and the sensor network have gained attention in scientific, technological, and research communities [2]. A wearable device displayed that the parameters record the data to track outside the laboratories; the devised solution will use the wireless sensor networking method with every sensor node (SN) wirelessly transferred to the coordinator utilizing the Wi-Fi network protocols [3]. The coordinator will serve as a router that connects SNs to an end device on the internet and mobile device or a computer [4]. On every sensor band, a pulse oximeter, a temperature sensor, a galvanic skin response sensor, and a heart rate sensor can be placed. The SNs can be linked to the human body and act entirely unheated. They were battery-powered. The compact shape and lightweight of the SNs make it easy to link to the body [5].
Heart diseases or otherwise known as cardiovascular diseases mostly refer to the conditions of narrowed or blocked blood vessels, that causes a stroke, heart attack, and angina or chest pain [6]. Other types of heart conditions affect the muscle or valve, rhythm of the heart causes other types of cardiovascular diseases [7]. However, machine learning (ML) is vital to determine whether anybody has suffered from cardiovascular disease. If these can be forecasted ahead of time, clinicians will have much time to obtain decisive data for diagnosing and treating patients. Heart disease is

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an inaccurate symptom of coronary artery diseases [8]. It can be called a cardiac disease; thus, it is not with cardiovascular diseases, which is disease that relates to any blood vessel. Artificial Intelligence (AI) seems to be intensely developed in more professional fields [9]. The foremost challenge of this study was to allot this advancement to the healthcare sector and particularly for the remote monitoring of patient health conditions. Certainly, the efficiency of clinical usage of Machine Learning (ML) techniques is well marked in decision-making, prediction, and classification of patient health conditions in accordance with a set of features attributes collected by using smart wireless interconnected sensor nodes [10]. Wireless Sensors Network (WSN) was approved as a substitute that could observe physiological conditions with the technological advancements in computer sciences, embedded systems, and wireless communication.

This article develops a Multi-sensor Data Fusion based Medical Data Classification Model using Gorilla Troops Optimization with Deep Learning (MDFMDC-GTODL) model. The presented MDFMDC-GTODL method enables collection of various daily activity data using different sensor devices which are integrated to produce high quality activities data. In addition, the MDFMDC-GTODL technique applies optimal attention based bidirectional long short term memory (ABLSTM) for predicting heart diseases. In this study, Gorilla Troops Optimization Algorithm based FS (GTOA-FS) approach is involved to improve the classifier outcomes. The experimental values of the MDFMDC-GTODL method are validated and the outcomes are examined under different prospects.

1. Related Works

In [11], the authors modelled a smart healthcare scheme to compute heart disease via feature fusion and ensemble DL method. For generating valuable healthcare information, initially, the feature fusion algorithm compiles the derived features from electronic medical reports as well as sensor data. Then, by choosing the significant ones and eliminating redundant and irrelevant features the information gain approach minimizes the computation burden and enhances the outcomes of the system. In [12], devised data fusion empowered Ensemble technique to deal with healthcare data acquired from BSN in a fog computing ecosystem. Day-to-day activities data will be gained through sensor collection which can be merged for generating high quality activity data. The information which is merged was after presented as an input to ensemble classification model for predicting cardiovascular disease at an initial level. The ensembles will be hosted in Fog computing ecosystem and predictive computations can be executed in a decentralised manner.

Al-Makhadmeh and Tolba [13] present an IoT-enabled medical device to gather heart details of patients that is before and after heart disease. The DL technique will learn cardiovascular disease features from previous analysis and attains efficiency through the effectual management of complicated data. In [14], presented fault-tolerant data processing methods (FTDPMs) to deal with irregular sensor data. The reliability of the recommendation will ensure the specific necessity for sensor data processing, modifying the mistakes. An SVM classifier was employed in this reliability prediction process. In [15], the authors proposed an IoMT structure for diagnosing heart disease by employing MSSO-ANFIS model. This fosters the searching ability utilizing Levy flight technique. The consistent learning procedure in ANFIS was based on gradient-related learning and it is stuck in local minima. The learning parameter can be maximized through MSSO for offering superior outcomes for ANFIS.

In [16], an IoT structure was devised for evaluating heart disease very accurately by utilizing a Modified Deep CNN (MDCNN). The ECG signals and blood pressure levels of patients can be monitored by the smartwatch and heart monitoring apparatus that is attached to the patients. The MDCNN can be used for categorizing the received sensor data into abnormal and normal. Through the comparison of the MDCNN with existing deep DL -NNs and LR, the system performance will be scrutinized. Yoo et al. [17] presented a model to detect the personalized heart condition in addition to the fast and effectual pre-processing approach and DNN for computing the real-time biosensor input data which is collected. A fast Fourier transform was implemented in pre-processing work for analyzing the pulse frequency. A DNN could make multiple layers and would execute an operation method of nodes by utilizing gradient descent.

2. The Proposed Model

In this manuscript, a new MDFMDC-GTODL approach was projected for automated medical data classification using sensors. The presented MDFMDC-GTODL algorithm enables collection of various daily activity data using different sensors which are then fused to produce high-quality activity data. Then, the data classification process encompasses the GTOA-FS technique, Adagrad hyperparameter tuning, and ABLSTM classification. Fig. 1 shows the workflow of the MDFMDC-GTODL method.

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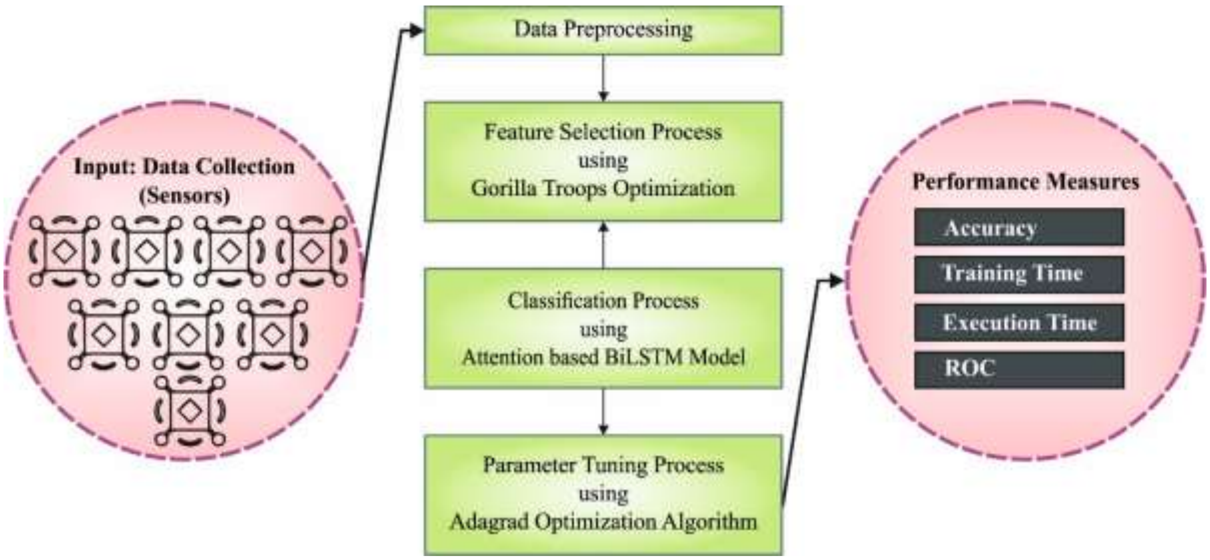

Figure 1: Overall process of MDFMDC-GTODL method

A. Data Collection and Data Fusion

In this work, the activity data will be collected using the wearable sensors (Fitbit 3, Misfit Shine 2, Jawbase, Whitings Puke). The sensor is placed in human body as this presented structure uses 5G network for transferring data from sensors to paired personal gadgets. The prediction task can be defined as a binary classifier task in which the existence of heart disease can be forecasted in an individual depending on the recorded activities. And deployed many bio-SNs on human objects. It can be assumed that every sensor would record single physiological sign called a feature. BSN will collect measurements periodically and data can be transmitted to the coordinator for data fusion process. Several smart gadgets involve mobile phones or medical devices used as coordinators.

Here $\mathrm{A} = \{\alpha_1, \dots, \alpha_m\}$ denotes the sensor and $\Gamma = \{\gamma_1, \dots, \gamma_m\}$ represents the respective weights so that $\sum \gamma = 1$. Assume that the sensor is functioning without failure, the resultant of the system can be calculated by,

$$\mathbb{O} = \{\alpha_1\gamma_1, \dots, \alpha_m\gamma_m\}.$$

If sensors fail at the time of operation, the resultant of the mechanism can be adjusted as,

$$\mathbb{O}' = \{\beta_1\gamma_{n1}, \dots, \beta_n\gamma_{ni}\}, \tag{1}$$

whereas γ_j denotes working sensors and $\sum \beta = 1$ was sustained. The weights can be dispersed homogeneously for every sensor, that is, $1/n$, for working sensor. If the sensor fails, the data of sensor was rejected. The data gained from other sensors will be inputted to the upgraded configuration (Eq.1) for processing data fusion.

B. Feature Selection using GTOA-FS Technique

At this stage, the GTOA is exploited to choose features. The GTOA technique comprises exploitation and exploration stages, Eqs. (2)-(13) defines the main concept of projected technique [18]. The exploration stage was utilized initially for implementing a global search space. It generates utilization of 3 important techniques like move to location of other gorillas, migrate to unidentified place, and migrate to identified place. The exploitation stage is written in the following.

$$GX(t+1) = \begin{cases} (ub - lb) \times r_1 + lb, & r < p, \\ (r_2 - C) \times X_r(t) + L \times H, & r \geq 0.5, \\ X(i) - L \times (L \times (X(t) - GX_r(t)) + r_3 \times (X(t) - GX_r(t))), & r < 0.5. \end{cases} \tag{2}$$

At this point, $X(t)$ is the gorilla's present place, and $GX(t+1)$ defines gorilla's place in $t+1$ iteration. p determines a variable betwixt zero and one determines the migration approach that chooses. lb and ub signify the lower and upper limits correspondingly X_r defines the arbitrarily selected gorilla member in the populations and GX_r stands for the arbitrarily selected in gorilla candidate place vector. r_1, r_2, r_3, and r depict the arbitrary value in zero and one, upgrade on every iteration. In addition, C, L, and H are measured as:

$$C = F \times \left(1 - \frac{It}{\text{Max } It}\right), \tag{3}$$

$$F = cos(2 \times r_4) + 1, \tag{4}$$

$$L = C \times l, \tag{5}$$

$$H = Z \times X(t), \tag{6}$$

$$Z = [-C, C]. \tag{7}$$

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In the expression, It represents the existing round and $MaxIt$ signifies the entire iteration amount. In Eqs. (4) and (5), r_4 and l stands for the arbitrary value betwixt in zero and one, upgrading on every iteration. In Eq. (7), Z depicts the arbitrary number lies in -C to C. followed by, during the exploration step, this technique measures fitness values of GX solution, and the fitness value was GX(t)<X(t), the X(t) solution was replaced by GX(t) solutions. The exploitation step of AGTO generates utilize of 2 approaches, competing with adult female gorilla and subsequent silverback gorilla. This technique was selected with related the C value with the parameter W set. If C≥W, the GTOA activities the subsequent silverback gorilla approach, once C<W, compete to adult female gorilla was desired. After the silverback gorilla was expressed as:

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t), \tag{8}$$

$$M = (|\frac{1}{N}\sum_{i=1}^{N} G\,X_i(t)|^{g})^{\frac{1}{g}}, \tag{9}$$

$$g = 2^L. \tag{10}$$

In Eq. (8), $X_{silverback}$ refers the silverback gorilla place. In Eq. (9), $GX_i(t)$ signifies the place of all the candidate gorillas from t iteration and N implies the entire count of gorillas. The competition with adult female gorillas was demonstrated under.

$$GX(i) = X_{silverback} - (X_{silverback} \times Q - X(t) \times Q) \times A, \tag{11}$$

$$Q = 2 \times r_5 - 1, \tag{12}$$

$$A = \beta \times E, \tag{13}$$

$$E = \begin{cases} N_1, r \geq 0.5, \\ N_2, r < 0.5. \end{cases} \tag{14}$$

In Eq. (12), r_5 demonstrates the arbitrary value in zero and one upgrading on every iteration. In Eq. (13), β represents the variables. In Eq. (14), if rand ≥0.5, E stands for the arbitrary number from the standard distribution and dimensional of problems, once rand<0.5, E signifies the arbitrary number chosen in a standard distribution. At last, during the exploitation step, this technique estimates fitness value of all GX solutions. Whereas GX(t)<X(t), afterward X(t) solution was replaced with GX(t) solution, and an optimal solution preferred in the total population was assumed that silverback gorilla.

The fitness function (FF) is applied to maintain a balance among the classifier accuracy (maximum) gained by utilizing selected features and the count of features chosen in every solution (minimal), Eq. (15) indicates the FF for evaluating solutions.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{15}$$

whereas $\gamma_R(D)$ denotes the classifier error rate. $|R|$ was the cardinality of the subset which is selected and $|C|$ denotes the overall features in the dataset, α, and β were 2 variables matching the significance of classifier quality and subset length. ∈ [1, 0] and $\beta = 1 - \alpha$.

C. Data Classification using Optimal DL Model

The ABLSTM method is used in this study for data classification, i.e. heart disease prediction. The LSTM method decided that information is preserved and applicable and information is removed according to the trained data [19-22]. The LSTM is widely employed in NLP tasks includes sentiment analysis, document classification, and so on. The LSTM cell exploited is forgotten, input, output, and layer, and it are mathematically expressed in the following:

$$f_z = \sigma\left(W_{fh}h_{z-1} + W_{fx}x_z + b_f\right) \tag{16}$$

$$i_z = \sigma(W_{ih}h_{z-1} + W_{ix}x_z + b_i \tag{17}$$

$$\tilde{c}_z = \tanh(W_{\tilde{c}h}h_{z-1} + W_{\tilde{c}x}x_z + b_{\tilde{c}}) \tag{18}$$

$$c_z = f_z.c_{z-1} + i_z.\tilde{c}_t \tag{19}$$

$$o_z = \sigma(W_{oh}h_{z-1} + W_{ox}x_z + b_0 \tag{20}$$

$$h_z = 0_z \cdot \tanh(c_z) \tag{21}$$

Now, x_z denotes the input; h_{z-1}, and h_z indicates the result of the preceding LSTM units and existing results; c_{z-1}, and c_z indicates the memory in last LSTM unit and cell state; f_z represent the forget gate values; W_i, $W_{\tilde{c}}$, and W_0 represent the weighted; b signifies bias. By incorporating the concept of LSTM and BRNN, it is possible to achieve BiLSTM that is more efficient and superior to LSTM from classification procedure, especially from data classification task. Fig. 2 demonstrates the architecture of Bi-LSTM method.

In the ABLSTM approach, attention methodology was exploited to assign dissimilar weights to terms contributed distinctly to sentiment of the text. The common way of allocating dissimilar weights to varied terminologies in a sentence was utilizing weighted incorporation of each hidden state, S_{A_W} in the following.

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$$\alpha_t = \frac{\Sigma xp(v^T \cdot \tilde{h})}{\sum_t \exp\ (v \cdot \tilde{h})} \tag{22}$$

$$S_{A_w} = \sum_t \alpha_t\, h_t \tag{23}$$

From the expression, $\tilde{h}$ and h can be well-defined and v refers to a trained parameter. To adjust the ABLSTM hyperparameters, the Adagrad optimizer is used in this work.

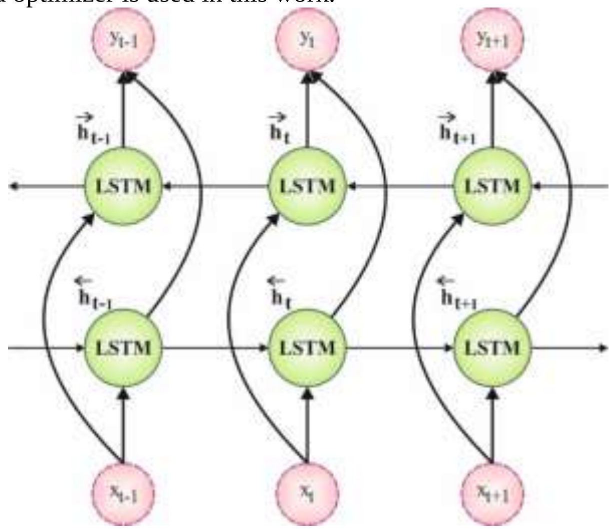

Figure 2: Structure of Bi-LSTM

In Adagrad optimizer, accumulate squared gradients and the gradients (g_τ) of all the variables at the iteration t can be formulated by:

$$G_t = \sum_{\tau=1}^{t} g_\tau \odot g_\tau \tag{24}$$

In Eq. (24), $\odot$ specifies a component wise multiplication and $g_\tau \in \mathbb{R}^{|\theta|}$ shows the gradient of the present at the τ iteration. The upgraded value of a variable ($\Delta\theta_t$) could be Adagrad is given below.

$$\Delta\theta_t = -\frac{\alpha}{\sqrt{G_t + \varepsilon}} \odot g_\tau \tag{25}$$

In Eq. (25). α represents learning rate and ε indicates a smoothing component which prevents division by zero. Meanwhile, the learning rate could be predetermined prior to training as.

$$\theta_t = -\alpha(\frac{1}{\sqrt{G_t + \varepsilon}} \odot g_\tau) \tag{26}$$

In Eq. (26), G_t denotes earlier gradient computation and gradient revision g'_t is denoted by:

$$g'_t = \frac{1}{\sqrt{G_t + \varepsilon}} \odot g_\tau \tag{27}$$

Thus, the Adagrad could be upgraded using the subsequent formula:

$$\Delta\theta_t = -\alpha g'_t \tag{28}$$

In Eq. (28), $\Delta\theta_t$ indicates upgraded value of parameter at iteration t and α denotes learning rate.

3. Results and Discussion

This section investigates the heart disease prediction outcome of the MDFMDC-GTODL model. The results are assessed under diverse number of features. Table 1 and Fig. 3 report a brief $accu_y$ inspection of the MDFMDC-GTODL method with ABLSTM model. The experimental values demonstrated that the MDFMDC-GTODL technique has reached maximum $accu_y$ values. For instance, with 2 features, the MDFMDC-GTODL model has attained increased $accu_y$ of 88.56% and the ABLSTM model has obtained decreased $accu_y$ of 74.99%. Along with that, with 4 features, the MDFMDC-GTODL model has achieved increased $accu_y$ of 95.21% and the ABLSTM method has acquired decreased $accu_y$ of 89.62%. In line with, with 10 features, the MDFMDC-GTODL model has attained increased $accu_y$ of 96.27% and the ABLSTM technique has gained decreased $accu_y$ of 93.48%.

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Table 1: Accuracy analysis of MDFMDC-GTODL method with ABLSTM system

No. of Features	ABLSTM	MDFMDC-GTODL
1	64.62	76.72
2	74.99	88.56
3	84.97	93.74
4	89.62	95.21
5	91.35	95.74
6	92.41	96.40
7	93.21	96.14
8	93.88	96.67
9	94.01	97.07
10	93.48	96.27
11	92.68	96.27

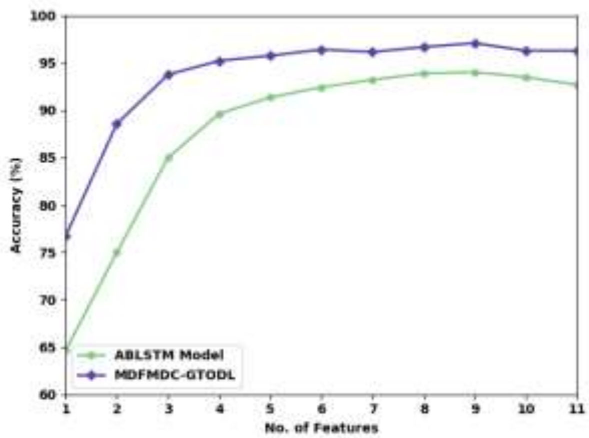

Figure 2: $Accu_y$ analysis of MDFMDC-GTODL approach with ABLSTM system

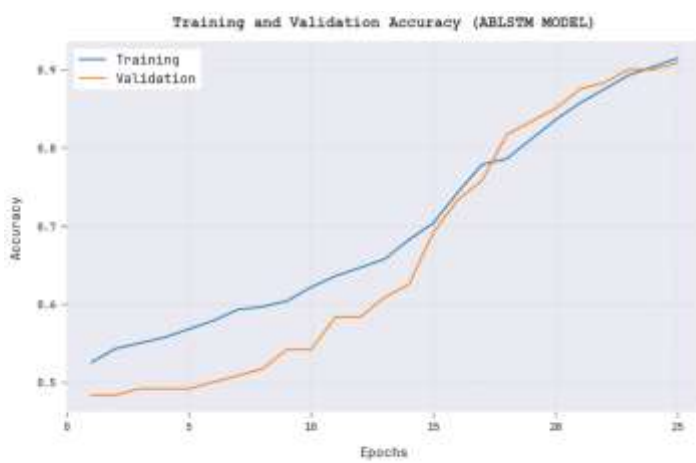

Figure 4: TR_{acc} and VL_{acc} analysis of ABLSTM method

Fig. 4 demonstrates the training accuracy (TR_{acc}) and validation accuracy (VL_{acc}) achieved by the ABLSTM method under test database. The simulation values denoted the ABLSTM approach has reached maximum values of TR_{acc} and VL_{acc}. Apparently, the VL_{acc} is better than TR_{acc}.

Fig. 5 exhibits the training loss (TR_{loss}) and validation loss (VL_{loss}) obtained by the ABLSTM method under test database. The simulation values showed the ABLSTM technique has established least values of TR_{loss} and VL_{loss}. Especially, the VL_{loss} is lower than TR_{loss}.

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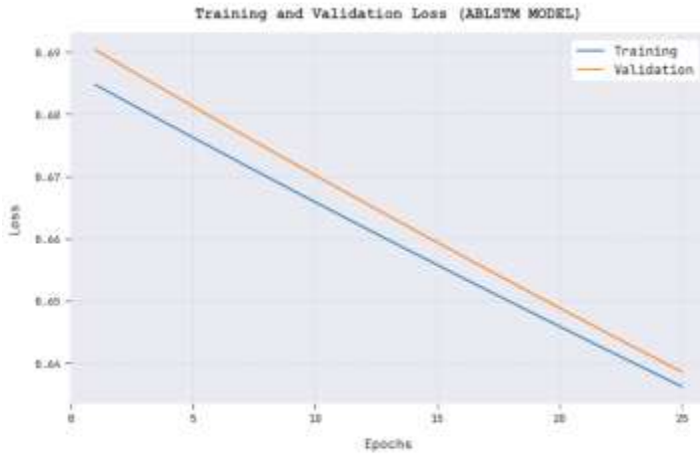

Figure 5: TR_{loss} and VL_{loss} analysis of ABLSTM method

Fig. 6 demonstrates The TR_{acc} and VL_{acc} attained by the MDFMDC-GTODL method under test database. The simulation values exemplified the MDFMDC-GTODL approach has attained maximal values of TR_{acc} and VL_{acc}. To be specific the VL_{acc} is greater than TR_{acc}.

Fig. 7 displays the TR_{loss} and VL_{loss} reached by the MDFMDC-GTODL technique under test database. The simulation value indicated the MDFMDC-GTODL method has exhibited minimal values of TR_{loss} and VL_{loss}. Especially, the VL_{loss} is lower than TR_{loss}.

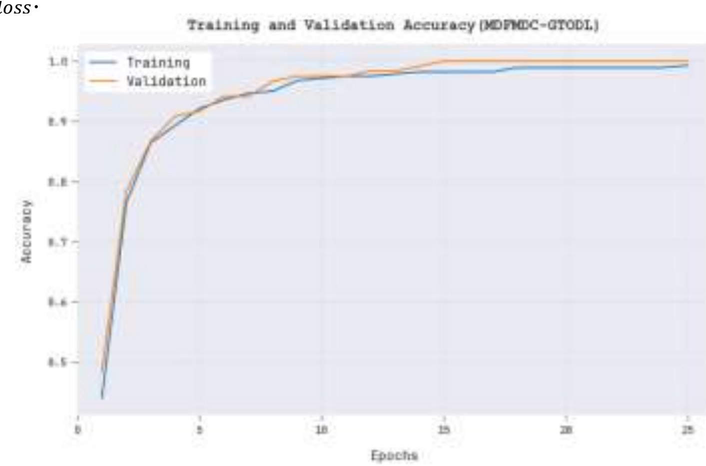

Figure 6: TR_{acc} and VL_{acc} analysis of MDFMDC-GTODL method

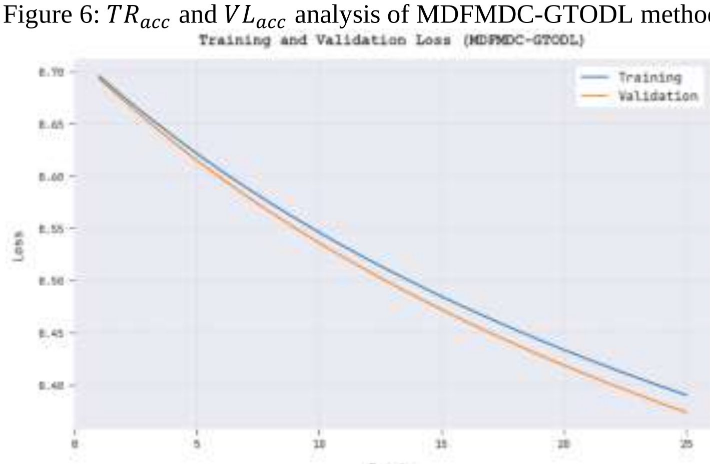

Figure 7: TR_{loss} and VL_{loss} analysis of MDFMDC-GTODL method

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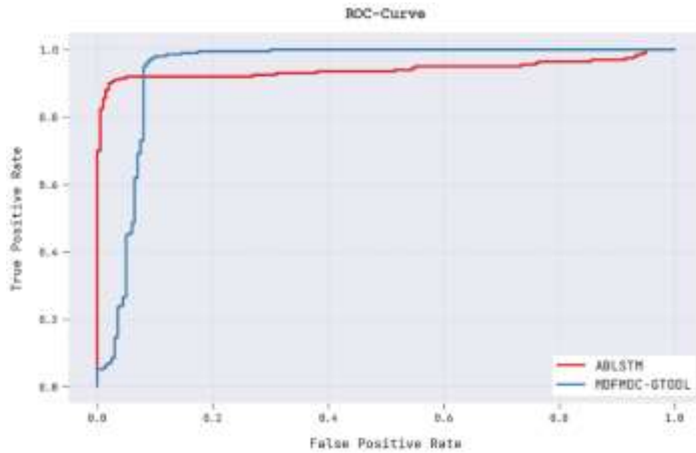

Figure 8: ROC study of MDFMDC-GTODL system with ABLSMT technique

A brief ROC analysis of the MDFMDC-GTODL technique under test database is portrayed in Fig. 8. The results indicated the MDFMDC-GTODL algorithm has exemplified its ability in classifying dissimilar classes under test database.

Table 2 and Fig. 9 offer a complete $accu_y$ examination of the MDFMDC-GTODL method with existing techniques. The simulation outcomes indicated the supremacy of the MDFMDC-GTODL method with boosted $accu_y$ values. With 2 features, the MDFMDC-GTODL model has provided increased $accu_y$ of 88.56% whereas the ABLSTM, keRF, and RF techniques have resulted in lessen $accu_y$ of 74.99%, 70.33%, and 64.88% correspondingly. Eventually, on 4 features, the MDFMDC-GTODL method has rendered increased $accu_y$ of 95.21% whereas the ABLSTM, keRF, and RF techniques have accomplished minimal $accu_y$ of 89.62%, 82.04%, and 77.78% correspondingly. Meanwhile, on 10 features, the MDFMDC-GTODL approach has presented increased $accu_y$ of 96.27% whereas the ABLSTM, keRF, and RF approaches have led to minimal $accu_y$ of 92.68%, 88.82%, and 85.36% correspondingly.

Table 2: Comparative analysis of MDFMDC-GTODL method with other existing techniques

No. of Features	ABLSTM	MDFMDC-GTODL	keRF Model	RF Model
1	64.62	76.72	59.83	56.50
2	74.99	88.56	70.33	64.88
3	84.97	93.74	76.72	72.60
4	89.62	95.21	82.04	77.78
5	91.35	95.74	85.50	82.31
6	92.41	96.40	88.82	83.90
7	93.21	96.14	90.29	87.36
8	93.88	96.67	90.68	87.09
9	94.01	97.07	90.82	87.23
10	93.48	96.27	90.02	86.30
11	92.68	96.27	88.82	85.36

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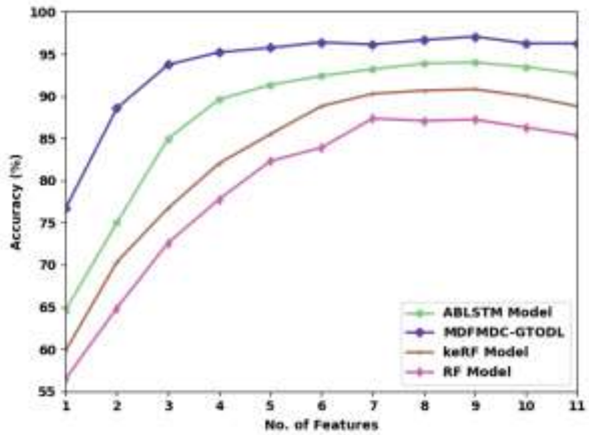

Figure 9: Comparative analysis of MDFMDC-GTODL method with other existing techniques

Table 3 and Fig. 10 shows a comparative execution time (EXET) inspection of the MDFMDC-GTODL model. The outcomes indicated that the MDFMDC-GTODL method has obtained minimal EXET values. For example, with 20% of data samples, the MDFMDC-GTODL technique has reached minimal EXET of 0.43s whereas the ABLSTM, keRF, and RF models have resulted to maximum EXET of 0.53s, 1.37s, and 1.51s respectively. Also, with 40% of data samples, the MDFMDC-GTODL method has attained minimal EXET of 0.64s whereas the ABLSTM, keRF, and RF approaches have resulted to maximum EXET of 0.95s, 1.73s, and 2.33s correspondingly. Furthermore, with 100% of data samples, the MDFMDC-GTODL approach has attained minimal EXET of 2.11s whereas the ABLSTM, keRF, and RF techniques have resulted to maximum EXET of 2.41s, 3.42s, and 3.84s correspondingly.

Table 3: EXET results of MDFMDC-GTODL system with other existing techniques

EXET (sec)				
No. of Samples (%)	ABLSTM Model	MDFMDC-GTODL	keRF Model	RF Model
20	0.53	0.43	1.37	1.51
40	0.95	0.64	1.73	2.33
60	1.48	1.24	2.37	2.56
80	1.95	1.76	2.88	2.93
100	2.41	2.11	3.42	3.84

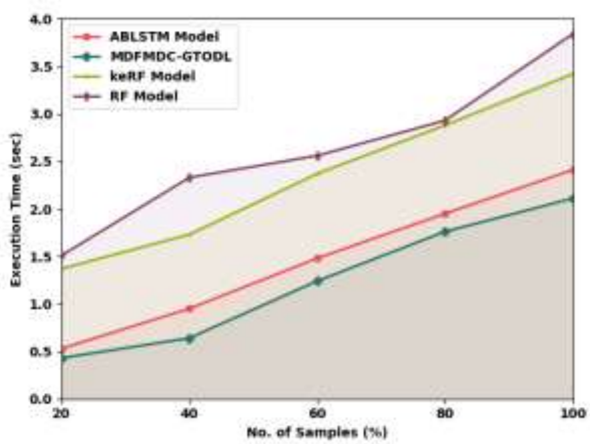

Figure 10: EXET analysis of MDFMDC-GTODL method with other existing techniques

A comparative training time (TRT) review of the MDFMDC-GTODL algorithm is made in Table 4 and Fig. 11. The outcomes shown the MDFMDC-GTODL method has reached minimal TRT values. For example, with 20% of data samples, the MDFMDC-GTODL technique has obtained minimal TRT of 0.29s while the ABLSTM, keRF, and RF models have resulted in maximum TRT of 0.62s, 1.38s, and 1.77s correspondingly.

Table 4: TRT results of MDFMDC-GTODL system with other recent algorithms

TRT (sec)

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No. of Samples (%)	ABLSTM Model	MDFMDC-GTODL	keRF Model	RF Model
20	0.62	0.29	1.38	1.77
40	0.89	0.58	1.77	2.26
60	1.34	0.95	2.17	2.68
80	1.90	1.64	2.60	3.24
100	2.42	2.12	3.12	3.58

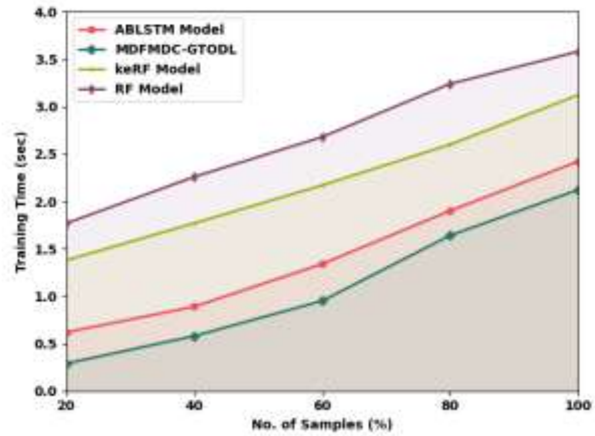

Figure 11: TRT analysis of MDFMDC-GTODL method with other existing techniques

Similarly, with 40% of data samples, the MDFMDC-GTODL method has obtained minimal TRT of 0.58s whereas the ABLSTM, keRF, and RF approaches have resulted in maximum TRT of 0.89s, 1.77s, and 2.26s correspondingly. Additionally, with 100% of data samples, the MDFMDC-GTODL method has obtained minimal TRT of 2.12s while the ABLSTM, keRF, and RF approaches have resulted in maximum TRT of 2.42s, 3.12s, and 3.58s correspondingly. From these results, it is concluded that the MDFMDC-GTODL model has obtained maximum performance over other techniques.

4. Conclusion

In this article, a new MDFMDC-GTODL approach was devised for automated medical data classification using sensors. The presented MDFMDC-GTODL technique enables collection of various daily activity data using different sensors which are then fused to produce high-quality activity data. In addition, the GTOA0FSBesides, the MDFMDC-GTODL technique employed the Adagrad optimizer with ABLSTM model for heart disease prediction. In this study, Gorilla Troops Optimization Algorithm based FS (GTOA-FS) technique is applied to improve the classification performance. The simulation outcomes of the MDFMDC-GTODL technique is validated and the outcomes are investigated in different prospects. The comprehensive comparative statement inferred the supremacy of the MDFMDC-GTODL method over other existing techniques.

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