

MAYFLY OPTIMIZED DEEP LEARNING FRAMEWORK IOT HEALTHCARE MONITORING

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Abstract – Internet of Things (IoT) systems continuously generate digital representations of people, objects or physical phenomena when they can be made available over the Internet. IoT provides powerful opportunities for seamless data collection and transfer of information, which is useful for healthcare providers to temporally diagnose patients remotely by analyzing their data from IoT information systems when they are far away. In this study, a mayfly optimized deep Learning framework, IOT Healthcare Monitoring (OLOHM) has been proposed to mitigate the risk of having event memory potential health issues and help Emergency services operate more effectively. The proposed method provides the real-time monitoring of health parameters, including the level of oxygen, pulse rate, and blood pressure, through the wearable sensors. These continuous vital readings are sent to cloud databases via gateway devices via Bluetooth or Wi-Fi. These data streams are pre-processed, and features extracted, and the Mayfly Optimization algorithm was utilized to optimize the use of features to ensure that the most appropriate features are considered. The appropriate features are put into a Bidirectional Gated Recurrent Unit (BiGRU) model to predict health status. The outputs are then available in real-time for healthcare providers, families, hospitals, and emergency services to react in a medically timely manner. This system achieves accuracies of 99.25% and over simple Hierarchical Hidden (SHH), and Deep Neural Network (DNN), and Bagged Decision Stump Decision Tree classifiers, again confirming the use of 95.23%, 98% and 97.35% respectively.

Keywords – Internet of Things, Bidirectional Gated Recurrent Unit, Mayfly Optimization, Healthcare, Deep Learning.

1. INTRODUCTION

The Internet of Things (IoT) has changed traditional healthcare systems into intelligent, connected systems by creating connectivity and the possibilities of remote access and constant monitoring of patient data [1]. For example, wearable devices and a variety of IoT-based medical technologies can extract physiological information from patients in real-time, for instance, blood glucose levels, body temperature, and so on; consequently, this level of connectivity enables the healthcare industry to provide fast diagnoses and clinical treatments off-site [3].

Remote health monitoring entails collecting physiological information, such as ECG signals, body temperature, saturation levels of blood oxygen, and heart beat rate; fundamental physiological data can be analysed for a healthcare manager to make conclusions on current or failing health, particularly in real-time to identify imminent health problems and act on them quicker than relating through another pathway to secure feedback [4,5]. Through the integration of IoT and deep-learning (DL) technologies, home-based medical models have advanced a long way to detect early stages of health conditions, and continuous assessments of patient cases can be identified [6-8]. Once the physiological data is captured and analysed, they are transferred to a remote server where a DL model proceeds to analyse the data, looking for patterns associated with certain health conditions [9,10]. It is apparent that DL models provide a level of efficiency but also can be decision-aided systems in the case they analyze many patients' datasets and extract features essentially characterized by a specific health problem [12]. It is beyond doubt that traditional healthcare models have challenges that prevent sufficient anticipation of measuring patients' health, which can interfere with the accuracy and efficacy of patient care [13]. To overcome these issues, a novel OLOHM approach is proposed. The main contribution is as:

- The proposed method allows for continuous, real-time monitoring of important health variables by using wearables for a personalized and proactive health strategy and early detection of possible health issues.
- Employing the Mayfly Optimization algorithm, the system efficiently pre-processes and extracts the most relevant health indicators from the collected data, enhancing the accuracy and reliability of health status predictions.
- The integration of the BiGRU model enables accurate prediction of the patient's health status.

- The proposed approach is evaluated using performance indicators, including accuracy, f1score, precision, and recall.

The remaining portion is arranged as below. The related work is covered in Part 2, and the OLOHM approach is defined in Section 3. The result and conclusion are defined in Parts 4 and 5, respectively.

2. LITERATURE SURVEY

In 2020, Souri, A., et al., [14] suggested an IoT-integrated student healthcare monitoring framework to monitor students' signs and predict biological and behavioral variations using smart healthcare approaches. After calculating the framework, the SVM attained an accuracy of 99.1%, demonstrating promising results for the intended need. The performance of the SVM outperformed other approaches, namely multilayer perceptron neural networks, random forests, and decision trees, indicating its effectiveness for this application.

In 2022, Chatrati, S.P., et al., [15] introduced a SHH monitoring system that examines the glucose levels at home and the patient's blood pressure and alerts the healthcare provider if an anomaly is detected. Use SVM classification algorithms to forecast the patient's diabetes and hypertension grade. Afterwards, evaluating all sorting strategies, the SVM was found to be the most ACU and hence utilized to train the models.

In 2022, Rajan Jeyaraj, P., and Nadar, E.R.S., [16] developed a DNN-based signal prediction and estimation technique. A smart monitor is a consumer gadget that has an intelligent sensor. A Smart-Monitor system was tested on two users by calculating the accuracy of physiological signal prediction. It was found that 97.2% of the results were accurate in the prototype experimental setup.

In 2023, Akhbarifar, S., et al., [17] developed a distant health monitoring model that incorporates a lightweight block encryption framework to ensure the security of health and medical data in a cloud-IoT. Based on the outcomes demonstrate that the K-star approach outperforms other classifiers, including MLP, RF, SVM, and J48, attaining an F-score of 93.99%, 95% accuracy, a recall of 93.5%, and a precision of 94.5%.

In 2023, Rajkumar, G., et al., [18] suggested a DL-based methodology for identifying heart disease. The results of the analysis show that the methodology used is superior to existing processes, with an error rate of 91.11% and an accuracy of 98.01%. Compared with the existing framework design, the experimental results demonstrate the high reliability for delivering reliable predictions about heart disease.

In 2023, Kumar, P. et al., [19] proposed a Blockchain-orchestrated Deep Learning framework (BDSDT) for coordinating the transfer of data in healthcare IoT data systems securely. The experiments conducted on dual public datasets, CICIDS-2017 and ToN-IoT, indicated that the proposed methodology provided high accuracy in two separate blockchain and non-blockchain experiments. The proposed methodology reaches an accuracy of 99% for the dual dataset to ensure high assurance in data transfers

through optimal utilization of the IOT environment, registering high assurance and trusting in the IOT environment.

In 2021, Khan, M.F. et al., [20] proposed Innovative medical care for older individuals. The research transforms medical science by increasing the quality of care to older adults, using ML algorithms. The experiments completed displayed the usefulness of the SHC model for monitoring adults, using IoMT datasets, and achieved a quite significant accuracy during validation, with an accuracy of 0.918

3. PROPOSED OLOHM

In this section, the OLOHM system is proposed for the advanced identification of the possibility of health issues and for improving the efficiency of emergency responses. The OLOHM system consists of a collection of various sensors worn by the patient to collect their health data in real-time. The sensors are made to send the raw data through gateways that are attached to the patient, like smartphones that use Bluetooth, Wi-Fi, or other wireless technologies. The health data collected produces a system message for storage and forwarding from the gateway, which sends health data to the cloud layer stored in a database. In the cloud layer, the raw data is pre-processed, and then it is used for feature extraction using Mayfly Optimization to select the key health indicators. The pre-processed data, after undergoing initial modifications using Mayfly Optimization formulae, are incorporated in a BiGRU model for health status prediction. The results of the BiGRU model, being the predicted health indicators, are sent back to the healthcare providers, family members, hospital, and emergency care providers, such as ambulances, empowered to continuously monitor the patients' health and respond early as needed. The workflow of the proposed system is illustrated in Figure 1.

3.1 Data Collection

The data collection mechanism is foundational to the IoT-based healthcare monitoring system because it involves the continuous sensing of the following critical health metrics by wearable sensors: blood pressure, temperature, oxygen level, and pulse rate, monitored in real-time for the above health details. The information obtained by the sensor will then be converted using a gateway device. In this study, the gateway was smartphones, using reliable communication protocols such as Bluetooth or Wi-Fi. This widely used process of data collection assures a continuous acquisition of accurate and up-to-date health information, which can be further processed or analyzed.

3.2 Data Pre-Processing

The current data preprocessing is the necessary step to pre-process the health data that was collected in order to conduct reliable health analysis and predictions. The data cleaning process, which involves checking for any noise, inconsistencies, or possible missing values; once little or no noise or inconsistencies were confirmed, this data was cleaned to ensure it is reliable. The second step of the data cleaning process is to normalize the data for consistency in the data. If they were both clean and normalized and begin to conduct feature extraction, which can also help in more accurate and reliable predictions

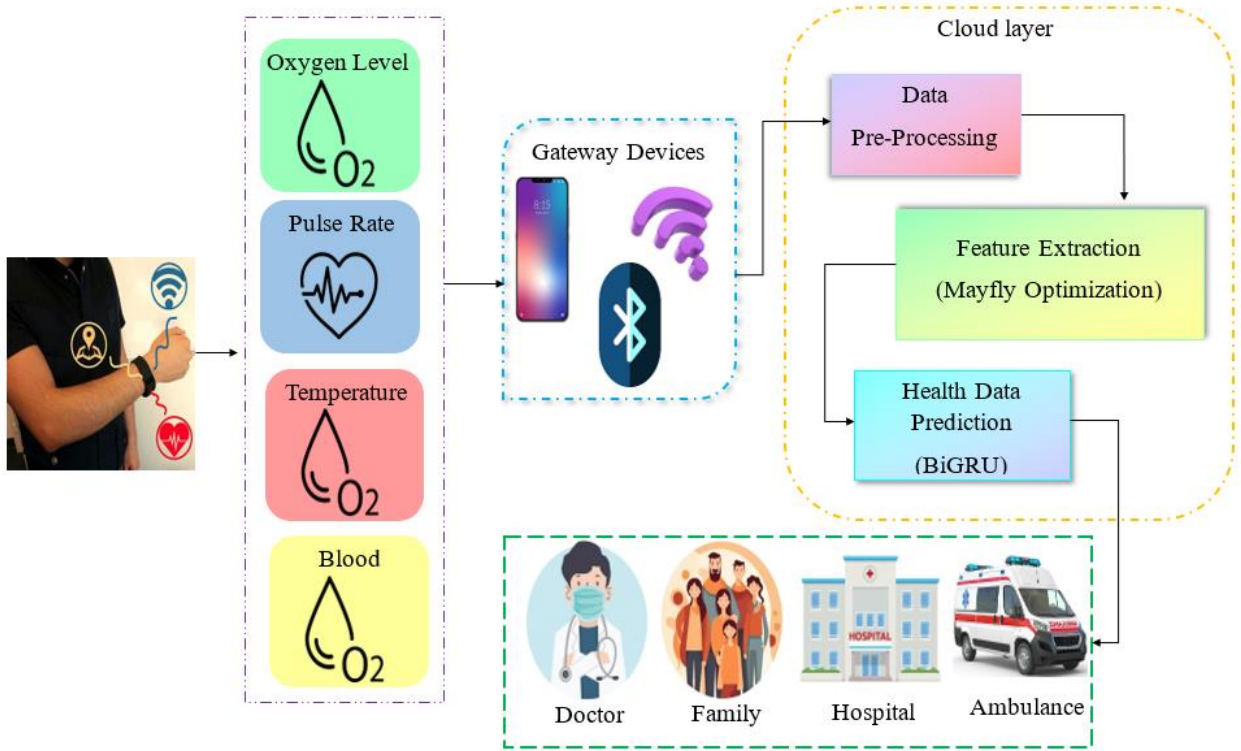


Figure 1. workflow of the proposed IoT-based healthcare monitoring framework

3.3. Mayfly Optimization for Feature Extraction

The pre-processed data is now fed to Mayfly Optimization (MFO) to extract the most suitable features. MFO was developed through imitation of the mating behavior of mayflies and their joint behaviour. At the beginning of the algorithm, there are two groups of males and females, first of all, which are known as mayflies. So, in a three-dimensional space, mayflies are concentrated in points randomly, and all of the candidates are expressed by $\varepsilon = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n)$. Then, the change of position is by the following velocity vector, expressed as $v = (v_1, v_2, \dots, v_n)$.

3.3.1 Movement of Male Mayfly

ε_m^t refers to the male mayfly position (m) at (t) time, and $v_{m\text{ male}}^{t+1}$ represents the velocity that can be included to ε_m^t . This will change the m-th distinct position. The t + 1 position of the male MF $\varepsilon(t + 1)$ can be defined as follows Eq. (1).

$$\varepsilon_m^{t+1} = \varepsilon_m^t + v_{m\text{ male}}^{t+1} \quad (1)$$

$pbest \in$

$$\{kbest_1, kbest_2, \dots, kbest_N, | \emptyset_{1, \dots, a} (abest)\} \text{ dominate } \{ \{ \emptyset_{1, \dots, a} kbest_1 \}, \{ \{ \emptyset_{1, \dots, a} kbest_2 \} \}, \dots, \{ \{ \emptyset_{1, \dots, a} kbest_N \} \} \} \quad (4)$$

where $(\emptyset_{1, \dots, a} : S^n \rightarrow s)$ denotes the objective functions. To provide the smooth operation of the algorithm, ideal mayfly population is always doing an up-and-down wedding dance. This indicates that the following procedure needs to be followed to modify the ideal mayfly's velocity:

$$v_{xy\text{ male}}^{t+1} = v_{xy\text{ male}}^t + p * \rho \quad (5)$$

Herein, d denotes the coefficient of the wedding dance, ρ indicates the random number at the range $[-1, 1]$, and

The following notation depicts the x^{th} MF velocity at the y^{th} dimension:

$$v_{xy\text{ male}}^{t+1} = v_{xy\text{ male}}^t + z_1 \exp(\alpha \rho_k^2) * (kbest_{xy} - \varepsilon_{xy}^t) + z_2 \exp(\alpha \rho_p^2) * (pbest_y - \varepsilon_{xy}^t) \quad (2)$$

The quantity $v_{xy\text{ male}}^{t+1}$ and ε_{xy}^t is the velocity and position of the x^{th} MF at the y^{th} dimension. z_i ($i = 1, 2$) indicates the constants of positive attraction. $kbest_{xy}$ and $pbest_y$ represent the places of local optimal and global optimal. α is a perceptibility constant. ρ^k and ρ^p represent the Cartesian distance from the x^{th} MF to the global and local optimal solution, respectively. The local optimal values $kbest_{xy}$ and global optimal values $pbest_y$, will be used for minimization problems based on Eq. (3) and Eq. (4).

$$kbest_{xy} = \begin{cases} \varepsilon_m^{t+1}, & \text{if } \{ \emptyset_{1, \dots, a} (\varepsilon_{xy}^t) \} < \{ \emptyset_{1, \dots, a} (kbest_{xy}) \} \\ \text{is kept the same otherwise} \end{cases} \quad (3)$$

$v_{xy\text{ male}}^{t+1}$ denotes the x^{th} male MF position at the y^{th} dimension.

3.3.2 Movement of Female Mayfly

Male mayflies gather in mobs, but females seek out males to mate with. The actual position with associated velocity of the x^{th} female mayfly at time t is set to v_x^t and $v_{xy\text{ male}}^{t+1}$, in that order. The position of the female mayfly (t + 1) is then represented as follows:

$$\varphi_m^{t+1} = \varphi_m^t + \varphi_m^{t+1} \text{female} \quad (6)$$

A deterministic scheme is used to characterize the attraction stage of the MA optimization process. It is very specific that the fitness function shows that limiting female individual area is more likely to lean towards the optimal male individual, the unless-optimal female individual would be more likely to lean towards the unless-optimal male individual, etc. Equation 7 can be used to determine the x^{th} female mayfly's velocity at the y^{th} dimension in relation to the minimization problem.

$$\begin{aligned} v_{xy \text{ female}}^{t+1} &= v_{xy \text{ female}}^t + z_1 \exp(\alpha \rho_{ij}^2) * (\epsilon_{xy}^t - \\ &\varphi_{xy}^{t+1}), \text{ if } \phi(\varphi_i) > \phi(\epsilon_n) \quad v_{xy \text{ female}}^t + rs * \rho, \\ &\text{ if } \phi(\varphi_i) \leq \phi(\epsilon_n) \end{aligned} \quad (7)$$

where $v_{xy \text{ female}}^{t+1}$ and φ_{xy}^t denotes the speed and position of the x^{th} female mayfly at the y^{th} dimension. ρ_{ij} measures the Cartesian distance from the x^{th} male and female mayfly. Rs denotes random walk coefficient.

Where the position and velocity of the x^{th} female mayfly at the y^{th} dimension are indicated by φ_{xy}^t and $v_{xy \text{ female}}^{t+1}$. The Cartesian distance from the x^{th} male and female mayfly is represented by ρ_{ij} . Rs stands for the random walk coefficient.

3.3.2 Mating of mayflies

Two parents are chosen from each of the male and female populations. Equations (8) and (9) are used to perform mating:

$$\text{offspring1} = \alpha * \text{male} + (1 - \alpha) * \text{female} \quad (8)$$

$$\text{offspring2} = \alpha * \text{female} + (1 - \alpha) * \text{male} \quad (9)$$

Currently, the individual's original velocity is zero.

3.4 Prediction via BiGRU

A key component of the prediction process is the BiGRU model, which makes use of its ability to detect both forward and backward temporal dependencies in health data. The BiGRU model processes the pre-processed and optimized data to produce extremely precise predictions of a patient's current state of health. A subset of recurrent neural networks (RNN) is GRU neural Systems. To address the problem, the standard RNNs suffer from gradient dispersion and rewrite their memory in unit steps. p_r shows the input vector, and the hidden state at time $r-1$ is represented by q_{r-1} and q_r gives the current GRU's output vector. At time r , GRU networks receive p_r and q_{r-1} , which results in output q_r . Formulas 11, 12, 13, 14 shows q_r defined as:

$$b_r = \sigma(Z_b p_r + S_b q_{r-1} + f_b) \quad (11)$$

$$d_r = \sigma(Z_d p_r + S_d q_{r-1} + f_d) \quad (12)$$

$$\tilde{q}_r = \tanh(Z_q p_r + S_q (q_{r-1} \otimes b_r) + f_r) \quad (13)$$

$$q_r = (1 - d_r) \otimes q_{r-1} + d_r \otimes \tilde{q}_r \quad (14)$$

Symbol σ is the Sigmoid function, which causes GRU neural networks to store or forget information. The elementwise production is $\otimes$, and the update and reset gates

are d_r and b_r , respectively. The notation, $\tilde{q}_r$ denotes the condition of the contestant at the time r . The input weights are Z_b , Z_d , Z_q , and cyclic input weights are S_b , S_d , and S_q . Finally, the offset vectors for Z_b , Z_d , Z_q , S_b , S_d , S_q are f_b , f_d , and f_r .

The BiGRU structure has 2 hidden layers, one forward and one backward. The data pattern is passed through both the forward and backward GRU layers

, which results in 2 symmetrical hidden layer states. We can symmetrically merge using both of those layer states, and after that take the average. Then, we can get the overall coding of the input text, as shown in equation (15):

$$Q_r = [\overrightarrow{Q_r} \oplus \overleftarrow{Q_r}] \quad (15)$$

4. RESULT AND DISCUSSION

The results of the OLOHM study are interpreted in this portion. The implementation with respect to multiple evaluation measures related to accuracy, recall, precision, and flscore. We compare the performance of the suggested model with that of the base systems: SHH, DNN, and BDSDT in relation to recall, precision, accuracy, and flscore.

4.1 Performance Metrics

The OLOHM framework is assessed using indicators of performance, which are accuracy, flscore, precision, and recall. In evaluating the metrics, relatively basic parameters can be used, including TrP, TrN, FalP, and FalN.

Accuracy: The most fundamental performance metric for correct sensor measurements. Accuracy gives relative improvement as false positives and false negatives are nearly equal in balanced sensor nodes. In this case, since it is relative to the value count, statistical accuracy should be indicated.

$$AC = \frac{TrP + TrN}{FalN + TrP + FalP + TrN} \quad (20)$$

$$PR = \frac{TrP}{TrP + FalN} \quad (21)$$

Recall: It is a ratio of positive feedback accurately forecasted by all actual observations that were collected in the course of class.

$$RC = \frac{TrP}{TrP + FalN} \quad (22)$$

F1 score: Recall and precision have been averaged and weighted. This score thus takes into account both false positives and false negatives.

$$F1S = 2 \times \frac{PR \cdot RC}{PR + RC} \quad (23)$$

4.2 Comparison Analysis

This section details the simulation of the suggested approach. The existing SHH, DNN, and BDSDT techniques are compared with the proposed method. The OLOHM approach is assessed utilizing accuracy, precision, recall, and flscore.

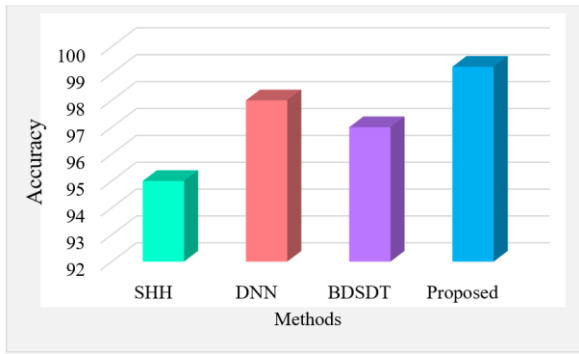


Figure 2. Accuracy Performance Comparison

Figure 2 compares the accuracy of four different methods including SHH, DNN, BDSDT, and Proposed Method. The suggested approach attains an accuracy of 99.25%. The suggested approaches achieve 99.25% accuracy, over SHH, DNN, and BDSDT which achieve 95.23%, 98%, and 97.35% respectively.

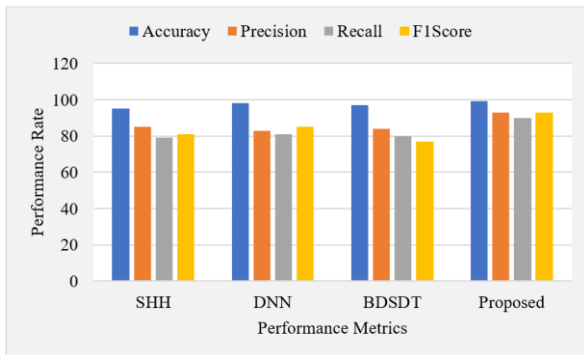


Figure 3. Performance Comparison

Figure 3 illustrates the performance of recall, accuracy, precision, and flscore with the proposed and existing techniques. For each classification technique, the flscore (F1S), recall (RC), precision (PR), accuracy (AC) and recall (RC) of the overall performance is evaluated using the TrP, TrN, FalP, and FalN. The accuracy, precision, recall, and flscore of the suggested framework are 99.25%, 90%, 95%, and 93% which is higher than the previous techniques.

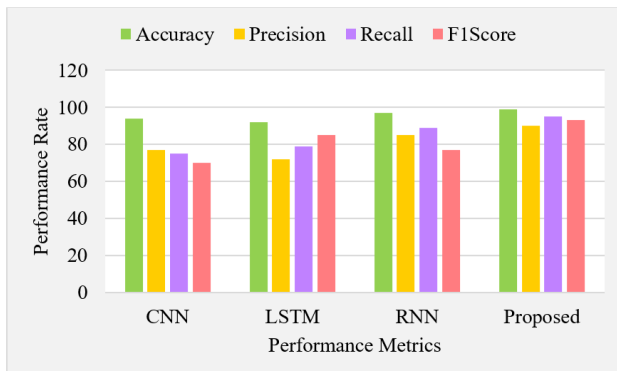


Figure 4. Comparison analysis of existing DL models

Figure 4 demonstrates the efficiency comparison of models including CNN, LSTM, RNN, and the Proposed model across numerous parameters such as F1 Score, Accuracy, Recall, and Precision. BiLSTM achieves 99.25%

accuracy, which is very high. The accuracy obtained by CNN, LSTM, and RNN is 94%, 92%, and, 97.1%.

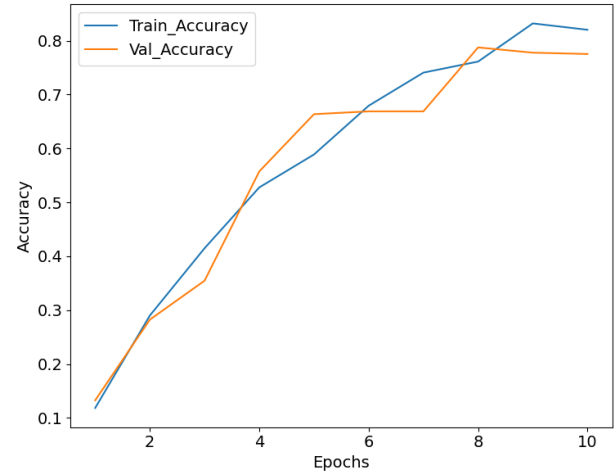


Figure 6. Accuracy of the suggested approach

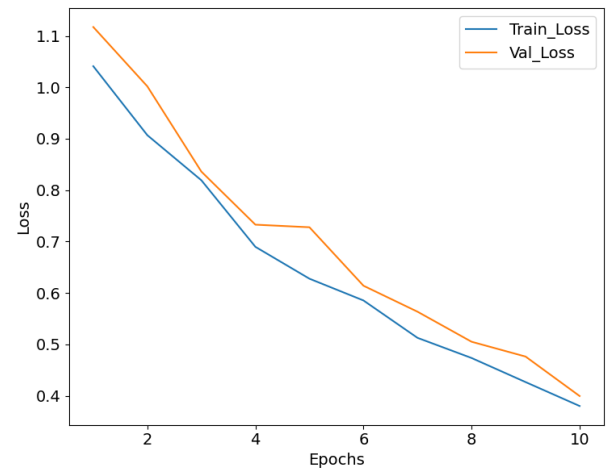


Figure 7. Accuracy of the suggested approach

The suggested framework has obtained an accuracy of 99.25%. The classification of the validation and testing is illustrated through accuracy and loss plots of suggested in Figures 6 and 7. These plots illustrate the model's performance highlighting its effectiveness in detecting intrusions. The low loss values also reflect successful learning with minimal overfitting during training.

5. CONCLUSION

In this paper, an OLOHM system has been proposed for the early detection of potential health issues and enhancing the efficiency of emergency responses. The system offers better accuracy in predicting health outcomes by combining wearable sensor technology with powerful cloud computing and deep learning. The integration of the Mayfly Optimization algorithm ensures that the system remains efficient by choosing the significant data features. The real-time accessibility of health data to healthcare providers and emergency responders improves patient care, particularly for individuals with chronic health status or those at risk of sudden medical emergencies. The proposed approaches achieve 99.25% accuracy, over SHH, DNN, and BDSDT which achieve 95.23%, 98%, and 97.35% respectively.

Future work will focus on expanding the system's capabilities to include additional health parameters and improving the adaptability of the DL model for a broader range of medical conditions.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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