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Classification of COVID-19 Cases using Deep Neural Network based on Chest Image Data through WSN

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Abstract: Due to the rapid spread of corona virus disease (COVID-19), it has been considered as a pandemic throughout the world. The misclassification of COVID-19 cases may even lead the death of the patients, and hence the diagnosis at early stage is important to stop further spread of the infection and to safeguard the life of the patients. This paper proposes the Aquila tuned Deep neural network (Aquila-DNN) classifier for the classification of COVID-19 patients using the chest image data assessed through Wireless sensor Network (WSN). The extraction of important features from the chest image data is important in the diagnosis as it encloses the important data of the patients. The optimal tuning of the DNN parameters using the Aquila Optimizer (AO) assists in improving the classification accuracy of proposed model. In addition, the convergence is also boosted using the tuning process of the AO algorithm. The effectiveness of the proposed Aquila-DNN model is validated with the analysis of the model based on the performance indices, namely accuracy, ROC curve, and F1 measure. The testing accuracy and the training accuracy of Aquila-DNN model are attained to be 99.7%, and 95.4545%, respectively.

Keywords: *COVID-19, Wireless sensor Network, chest image, Deep neural network, and Aquila Optimizer algorithm*

1. Introduction

WSNs are the networks of wireless embedded systems that generally function with attached sensors. WSNs acts as a demanding field of research, as they are broadly used in screening, manufacturing, military, healthcare, and so on. Among the developments in monitoring WSNs, collection and aggregation of the sensor data, such as patient data, environmental data, battlefield data, and so on plays a vital role for investigation. In order to precede this, the development of WSN gateway is important for the collection of data. A WSN gateway is nothing but a connection of WSN to Internet, where users of remote places can recover WSN data easily through the Internet and analyze the gathered data either offline or online. There are four principal elements in WSN. The first element is the WSN motes and their request code for sampling of data and communication. The second element is the sink node of WSN and its code to gather data and transfer to gateway model. The next one is the gateway organization, responsible for collecting the information from sink, performing the initial processing needs, storing the data, and transmitting to the data to the application. The fourth or the important component of WSN is the data organization system that obtains the data and offers functionalities to monitor the live data for evaluation and send back the data to database [1].

Automating the analysis of various diseases based on artificial intelligence (AI) has shown its effectiveness and better presentation in the categorization of images automatically using various machine learning strategies. Furthermore, machine learning describes the models that possess the capability of making decisions in the presence of large number of data samples. AI performs predictions and evaluations by testing the data input and executing functions that need human intervention particularly in the area of medicine.

Deep learning is an advanced model of classifying images and has revealed immense accomplishment in various applications, specifically in health-related applications [2,3]. It proficiently develops strategies that generate precise outcomes in calculating and categorizing the diseases with the aid of images as in brain tumor, liver diseases, pneumonia, lung cancer [4,5,6,7], and newly COVID-19 analysis, without the need for any human interference. The key motive for the use of deep learning is that it learns by developing a more abstract illustration of input data and assist in maximizing the accuracy of the model [8].

This paper introduces a deep learning model to classify the persons affected with COVID-19 using the chest image data collected through WSN network. The deep neural network classifier executes the classification process in an effective way with the tuning of the weights optimally using the Aquila optimizer. The significance of the proposed model depends on the use of the Aquila optimizer that assists in enhancing the effectiveness of proposed classification model. The WSN collects the chest image data of the patients and transfers the data to execute the image classification process with the aid of the

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selection of the cluster head in each cluster based on the energy level of the nodes. This research provides a detailed explanation of proposed model, and with the results, the effectiveness of the proposed classification model can be validated. Furthermore, comprehensive evaluation is provided on the basis of the performance of the existing classification strategies to analyze the superiority of the proposed methods of COVID-19 case classification.

The contribution and the key topics discussed in the study are,

 The proposed model designs an automated deep strategy model to classify the COVID-19 cases using the cheat images gathered through WSN network.

- ➢ The CH selection in each cluster for the energy efficient transfer of data is important in assessing the data through WSN.
- ➢ The weights of the DNN are optimally tuned using the Aquila optimizer algorithm for the improvement of classification accuracy.
- ➢ The proposed model is analyzed with the conventional strategies in terms of performance measures to authenticate the effectiveness of the proposed strategy.

The rest of the paper is organized as: section 2 presents the survey of the recent strategies of COVID-19 classification with the challenges associated with them section 3 describes the proposed optimization tuned deep learning model in COVID-19 patient's classification. Section 4 deliberates the outcomes of the proposed model, and section 5 concludes the paper.

2. Literature survey

This section deliberates the existing methods of COVID-19 case classification and the challenges associated with the existing model that acts as the motivation for the development of the proposed model.

2.1. Related works

The literature review of the existing methods is stated as, Dina M. Ibrahim *et al.* introduced a multi-classification deep learning model that provided enhanced performance in detection of COVID-19 cases. Similarly, the authors Thirukrishna *et al.* [9] developed a real time health monitoring framework that involves in detecting the health conditions of the patients. The health states, like body temperature, pulse rate, and electrocardiograph with the aid of various bio sensors can be made with better accuracy using the developed model. Abdul Awal *et al.* [10] designed the ADAptive SYNthetic (ADASYN) framework, which can also be used for the detection of diseases other than COVID-19, such as asthma, diabetics, and so on. An efficient method, named Decompose, Transfer, and Compose (DeTraC) on the basis of Deep convolutional neural network (Deep CNN) was introduced by Asmaa Abbas*et al.* [11], which provided robust and enhanced solutions in the classification of COVID-19 patients. Additionally, this method was able to cope with limited number of image data and even the irregularity of images. Another deep learning based method was introduced by Pathak *et al.* [12] that was efficient in reducing the attributes in the network that assist in enhancing the performance of the classification model. Nora El-Rashidy *et al.* [13] designed a end-to-end framework for COVID-19 case classification that assisted in providing an absolute Electronic Health Record (HER) system of the patients leading a way for even the non-expert physicians to make proper decisions to save a life of patients. Majid Nour *et al.* [21] introduced a model on the basis of CNN architecture that can routinely disclose the different features on chest X-ray images using its convolution with rich filter families, idea, and weight-allocation features. Gaurav Dhiman *et al.* [22] designed a deep learning and multi-objective optimization based strategy for identifying the patients infected with coronavirus using X-rays. The method is highly beneficial for real-time COVID-19 disease categorization from X-ray chest images.

2.2. Comparative table

The comparative table describing the advantages of the existing methods is given in table 1. Even though, each conventional method of COVID-19 classification is better in certain aspects, there exists number of limitations, in terms of convergence, computation time, and memory, which can be rectified using the proposed Aquila-DNN method. The proposed method overcomes such drawbacks with the significant act of controlling the weight parameters of DNN using the AO algorithm. In addition, the proposed method is capable of attaining an improved accuracy of 99.7%, which is high as compared with the existing methods.

Table 1. Describing the advantages of the existing methods

S.No	Author name	Technique used	Highlights	Achievements
1	Thirukrishna *et al.* [9]	Real time health monitoring framework	The method can detect patient's health conditions, like pulse rate, body temperature and electrocardiograph using different bio sensors	Accuracy=96.2%
2	Abdul Awal *et al.* [10]	ADAptive SYNthetic (ADASYN)	It can be noted that the framework can not only be applied to COVID-19 detection, but also applied to other classification Problems, such as diabetic prediction, asthma prediction, and so on.	Accuracy=98.5%
3	Asmaa Abbas *et al.* [11]	Deep CNN, called Decompose, Transfer, and Compose (DeTraC)	*DeTraC* showed effective and robust solutions for the classification of COVID-19 cases and its ability to cope with data irregularity and the limited number of training images too	Accuracy=82.75%
4	Pathak *et al.* [12]	Deep transfer learning technique	The method can more effectively reduce network attributes	Accuracy=96.22%
5	Nora El-Rashidy *et al.* [13]	End-to-end framework	The framework aimed to provide a complete EHR system that could benefit from all patients' data and help non-expert physicians to take the right decision to save a patient's life	Accuracy=97.78%
6	Majid Nour *et al.* [21]	CNN architecture	The method can routinely disclose the different features on chest X-ray images	Accuracy=96%
7	Gaurav Dhiman	Learning and multi-objective	The method is highly beneficial for real-time COVID-19 disease	Accuracy=97%

et al. [22]	optimization based strategy	categorization from X-ray chest images

2.3. Problem statement

The challenges associated with the existing methods of COVID 19 classification are deliberated as,

- With less accessibility of annotated images in medical field, the categorization of medical images acts as the major challenge in disease analysis.
- The Reverse Transcription Polymerase Chain Reaction (RT-PCR) strategy is a COVID-19 prediction model that possesses increased effectiveness in prediction. However, these testing equipments fail to satisfy the increasing requirement with its limited availability, specifically in developing countries.
- A sHapely Adaptive explanation (SHAP) evaluation measures does not present causality. Only the behavior and of the model and the data required to develop the model are described. Furthermore, the strategy does not envisage all the COVID cases correctly and is probable to obtain certain number of false negatives and positives.
- The occurrence of irregularities in data, especially in medical imaging processes, remains a tedious issue that generally ends up with mis-calibration among the various classes in the dataset.

3. Proposed COVID-19 Classification Model using WSN Assisted Data

At present, the world undergoes a pandemic condition with the widespread of corona virus, otherwise named as COVID-19, which is an acute respiratory disease. The COVID-patients are advised to isolate themselves isolated from others in such a way to control its transmission, as the disease is highly contagious. The people affected with COVID-19 are needed to be detected as soon as possible, to prevent others from being infected, deteriorating livelihood, life, and the economy. An optimization tuned deep learning model is proposed in this research to classify the patients affected with COVID-19 with the aid of chest images collected from the patients through WSN network. The schematic representation of proposed model is depicted in Figure 1.

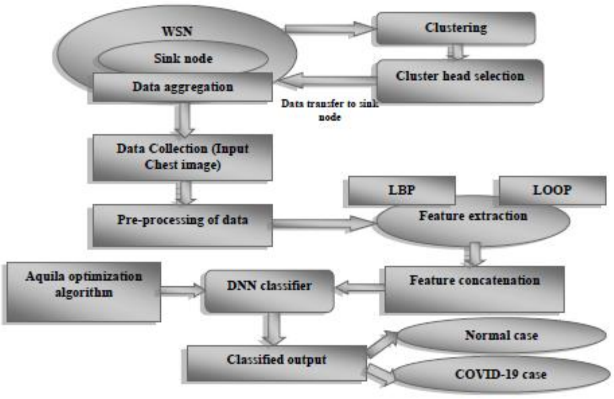
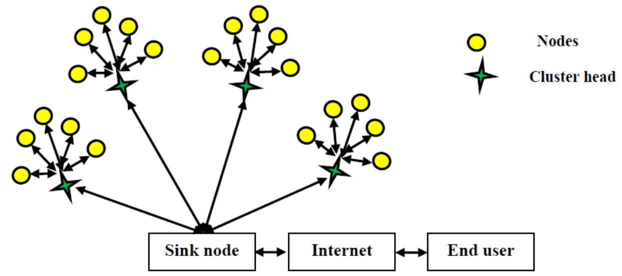


Fig. 1. Schematic diagram of proposed classification model

In the initial step, the nodes of WSN are subjected to clustering based on distance. Then the node possessing maximum energy is selected as the CH in each cluster, through which the data is send to the sink node of the WSN. Data aggregation process is carried out to present the gathered data in a summarized format in the sink node. The chest image data are collected from the sink node in such a way to process them to classify the patients with and without COVID-19. The chest data is then pre-processed to remove the artifacts and the unwanted background present in the image. Then the important texture features, such as Local binary pattern (LBP) and Local Optimal Oriented Pattern (LOOP) of the input image are extracted using the feature extraction process. The features thus extracted are then concatenated to form the feature vector that acts as the input to the DNN classifier [14], the weights and the parameters of DNN are tuned optimally using the Aquila Optimizer (AO) Algorithm [15] for the enhancement of the classification accuracy.

3.1. WSN network

The energy efficient data transfer is important for the effective assessment of data in the WSN network that helps in obtaining the classification results of the proposed COVID-19 classification model. The WSN comprise of a number of smart components that are interlinked through the internet, where the Base station (BS) function as the center of the network and is interlinked with the CHs, which possess certain number of sensor nodes. The links among the nodes perform direct transfer of data within certain range. Each node possesses a maximum level of data transfer, and



furthermore, each node consists of a unique ID and certain number of nodes that structures a cluster. The typical arrangement of WSN is shown in Figure 2.

Fig. 2 Typical arrangement of WSN

3.2. Cluster Head selection

In order to assure energy efficiency in the transfer of data, the clusters are formed with a CH in the proposed classification strategy. The optimal position of the nodes and CHs is responsible for the conservation of energy, where energy, distance and delay constitute the major role. The CH in each cluster collects the data from all the nodes in the cluster, during which the CH slumps its energy to a huge level compared to other nodes of the cluster. The deterioration in energy of CH is handled in the proposed model by constantly replacing the CHs, such that the node in the cluster possessing maximum energy and optimal distance from that of the BS replaces the existing CH. The CH replacement procedure is screened at the end of every transmission to ensure better transmission of data.

3.3. Data aggregation process

After the selection of CHs, date aggregation is performed in CHs to regularize the collected data in the sink node. The importance for the usage of data aggregation model is to maximize the energy efficiency of the nodes of the cluster. In the proposed classification model, data aggregation is used to remove the replicated data among the collected data through the CH, so as to evade the issue of communication delay that arises in the network [6]. The aggregated data in the sink node acts as the storage medium from where, the chest image data of the patients are collected to be processed to execute the classification task.

3.4. Pre-processing of image data

The chest image data accessed from the sink node are initially pre-processed to remove the artifacts that are present in the images enclosing non-stationary and nonlinear constituents. The need for the pre-processing step is to improve the accuracy in classification of the proposed DNN classifier. The raw chest image data of the patients is normalized using this step in such a way to make it suitable for the extraction of important features from the image using the feature extraction strategies [15].

3.5. Feature extraction

The pre-processed image data is then subjected to feature extraction process, in such a way to extract the significant features needed for classification process. The feature extraction process is the characteristic evaluation of the image used in the proposed classification module. The features that are considered to be extracted in the proposed system are the LBP, LOOP, and the texture features.

a) Local Binary pattern feature

LBP is an uncomplicated and effective texture feature operator of an image that makes the pixels of the image with the threshold of neighbourhood of each pixel and produces a binary output. The LBP detains the dissimilarity patterns equivalent to the image intensity and possess the differentiated features of the image [16]. The dimension of the LBP feature is $|1 \times 1000|$ and the feature thus obtained is indicated as R_B.

b) Local optimal-oriented pattern feature

LOOP is defined as the non-linear combination of the descriptors, such as LBP and LDP in such a way to overcome the drawbacks associated with the concept of LBP. The drawbacks, such as inaccurate binary measure of LBP, and the self-imposed limits of LDP is solved using the concept of LOOP. The LOOP descriptor programs the invariance in rotation as the major formulation and cancels out the empirical task of the measure of LDP parameter [16]. The dimension of the LOOP feature is $|1 \times 1000|$, and the feature thus obtained is indicated as R_O.

c) Development of feature vector

The feature vector is obtained from chest image data that contains the important data of the patient related to COVID-19 to be examined. The extracted features are combined together to create the feature vector that acts as the input to the DNN model, and the feature vector thus developed is expressed as,

$$R = \{R_B, R_O\} \tag{1}$$

The feature vector constitutes the characteristics of the significant features of the chest image data, and the dimension of the feature vector is $|1 \times 2000|$. The feature vector is then fed as the input to the DNN network, which classifies the input chest image of the patients either as normal case or COVID-19 case.

3.6. Aquila Optimization tuned deep neural network in COVID-19 case classification

The feature vector taken from the chest image data is the input to the DNN classifier for the classification of COVID-19 cases. Neural networks (NN) in the presence of multiple layers are termed as DNN that imitayes the biological structure of NN and allow a computer device to execute the classification tasks. The operating principle of DNN [17] involves in the use of current output layer as the input to the consequent hidden layer. The relation among the input feature R and the outcome of the initial hidden layer f(v) is formulated as,

$$f(v) = M\left(W^T R + bias\right) \tag{2}$$

where, R is the input to the neuron, W is the weight matrix and bias is the bias vector of initial layer, M is a non-linear function, and M(③) indicates the activation function. Each neuron attains number of inputs, and generates a single output. The output from one layer operates as the input of next layer. However, if a single neuron is made to accept the entire features of the image, there arise issues related to memory and computation. The neurons are thus shared using separate weight vectors, which are tuned using the Aquila optimization for enhancement of the classification module. The layers with convolution shared weights are termed as convolutional layers, and the layers without convolutional layers are termed as fully connected layers. Furthermore, the max pooling layer enhances the robustness of the model over noise. Finally, the last layer termed as the softmax layer normalizes the outputs and sums them to one. Thus, the output layer acts as a probability distribution with each neuron comprising the probability to a particular class. The parameters and the weights of the DNN are trained and found optimally using the Aquila optimization algorithm.

a) Aquila Optimization algorithm in tuning of parameters

Table 2. Pseudocode of AO algorithm

Sl. No	Pseudo code of proposed AO algorithm
1	Initialize population of Aquila optimizers
2	Initialize maximum iteration $Iter_{\max}$
3	**While**
4	Termination condition not met
5	Evaluate fitness function for all solutions
6	Update the Initial position
7	**For** all Aquila optimizers
8	Update the position by means of equation (3)
9	Check for fitness measure
10	**If**
11	$fitness_{old}$ is better than $fitness_{new}$
12	Maintain the old solution as the best solution
123	**Else**
14	Update the new solution as the best solution
15	**End If**
16	**End For**
17	**End While**
18	**Terminate**

The tuning of DNN parameters based on Aquila optimizer depends on the characteristics of traversing velocity and to-and-forth hunting feature of the Aquila optimizer. Due to the intelligence in hunting, the Aquila optimizers are considered to be the most analyzed creatures throughout the world. The male Aquila optimizers are highly efficient in hunting as compared to the female ones. The hunting methods used by the Aquila optimizers depend on four different models, where the Aquila optimizer switches between any of the four types based on the need to catch the prey [18]. The best update of position of the Aquila optimizer, where the Aquila optimizer attack the prey by dragging the prey out of coverage area is expressed as,

$$A_k^{b+1} = T_{QF} \times A_{best}^b - \left(X_1 \times A_k^b \times N_1\right) - X_2 \times levy(\alpha) + N_2 \times X_1 \tag{3}$$

where, A_k^{b+1} represents the position of the Aquila optimizer at

$(b+1)^{th}$ iteration, A^{b}_{best} is the best solution obtained so far in the b^{th} iteration, T_{QF} indicates the quality function related to search models, X_1 indicates the different movements of the Aquila optimizer, X_2 is a random number decreases gradually to 0 from 2, N_1 and N_2 are the random numbers that vary between 0 and 1, and $levy(\alpha)$ is the levy flight distribution. The pseudocode of the AO algorithm is given in table 2.

4. Results and Discussions

The results obtained using the proposed method of COVID-19 case classification is deliberated in this section.

4.1. Experimental setup

The experimentation of proposed Aquila-DNN classifier is executed in PYTHON tool installed in Windows 10 OS and 64-bit OS with 16GB RAM.

4.2. Dataset description

The COVID-19 Radiography Database [18] is used in the proposed classification model that comprise of the chest X-ray images of 219 COVID-19 positive cases, 1345 viral pneumonia images and 1341 normal images.

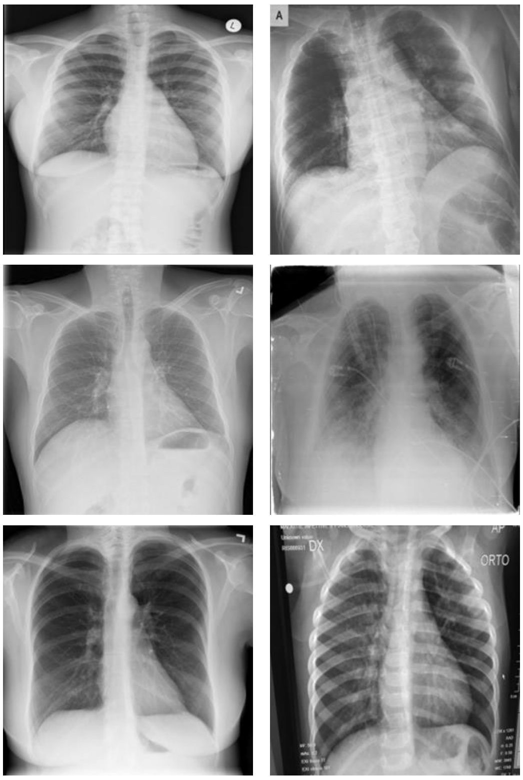
4.3. Experimental results

The experimental results obtained through the proposed Aquila Optimization-based DNN classifier for three cases is depicted in figure 3. Figure 3a accounts the normal image for three cases, and the corresponding COVID-19 images are depicted in figure 3b.

Patient 1

Patient 2

Patient 3



(a) (b)

Fig. 3 Experimental results, (a) Normal image, and (b) COVID-19 image

4.4. Evaluation metrics

The effectiveness of proposed Aquila Optimization-based DNN classifier is tested using the metrics described as below,

a) Accuracy: The rate of correct classifications out of the total data considered for classification are termed as training accuracy, whereas the testing accuracy is the count of exact decisions made by the testing instances over the total number of testing instances.

b) ROC curve: The description of true positive rate over the false positive rate is termed as the ROC curve, and it shows the relation among sensitivity and specificity.

c) F1 score: The measure of accuracy of a model is termed as F1 score, and it is the mean of precision and recall.

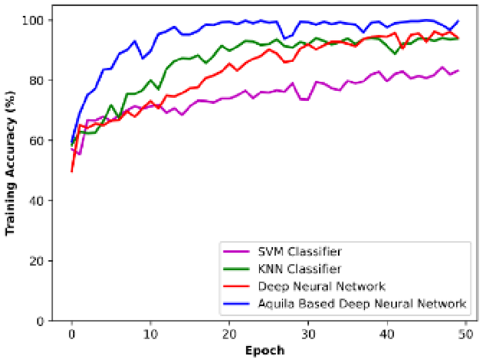
4.5. Comparative analysis of methods involved in COVID-19 case classification

The performance of Aquila-DNN is evaluated against the existing methods, such as Support vector machine [19], K-nearest classifier (K-NN) [20], and the DNN in terms of the performance indices is shown in figure 4. Figure 4a depicts the evaluation in terms of training accuracy. The training accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 10 is 70.5212%, 76.759%, 70.684%, and 87.2964%, respectively. The training accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 20 is 73.9414%, 91.5798%, 82.899%, and 99.3485%, respectively. The training accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 30 is 78.9902%, 90.9283%, 86.4821%, and 95.114%, respectively. The training accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 40 is 81.9218%, 94.0228%, 94.4625%, and 99.1857%, respectively. The training accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 50 is 83.2248%, 93.8599%, 94.1368%, and 99.6743%, respectively.

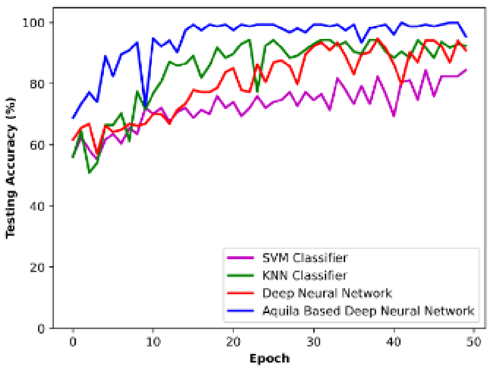
Figure 4b shows the analysis in terms of training loss. The training loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 10 is 56.2754%, 46.0972%, 57.4512%, and 29.5298%, respectively. The training loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 20 is 57.3147%, 16.5476%, 41.0002%, and 3.2645%, respectively. The training loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 30 is 47.6565%, 18.3086%, 30.7188%, and 17.7103%, respectively. The training loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 40 is 41.5103%, 8.7855%, 16.3812%, and 3.0604%, respectively. The training loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 50 is 37.8824%, 7.8836%, 15.393%, and 1.0811%, respectively.

Figure 4c shows the analysis in terms of testing accuracy. The testing accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 10 is 72.0779%, 71.6234%, 66.8831%, and 72.7273%, respectively. The testing accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 20 is 72.0779%, 88.5065%, 83.7662%, and 99.3506%, respectively. The testing accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 30 is 72.7273%, 89.1558%, 79.8701%, and 98.0519%, respectively. The testing accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 40 is 82.4675%, 94.3506%, 94.8052%, and 98.7013%, respectively. The testing accuracy of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 50 is 84.4156%, 92.4026%, 90.9091%, and 95.4545%, respectively.

Figure 4d shows the analysis in terms of testing loss. The testing loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 10 is 60.2596%, 49.597%, 59.8183%, and 72.479%, respectively. The testing loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 20 is 59.4544%, 22.8929%, 40.6827%, and 4.9227%, respectively. The testing loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 30 is 62.1752%, 26.4891%, 38.6676%, and 6.8797%, respectively. The testing loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 40 is 46.5643%, 7.326%, 17.2713%, and 3.3397%, respectively. The testing loss of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN for the epoch of 50 is 45.7367%, 13.1064%, 25.6678%, and 13.6792%, respectively.



(a)



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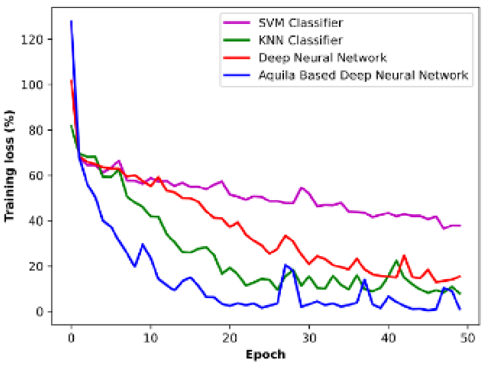
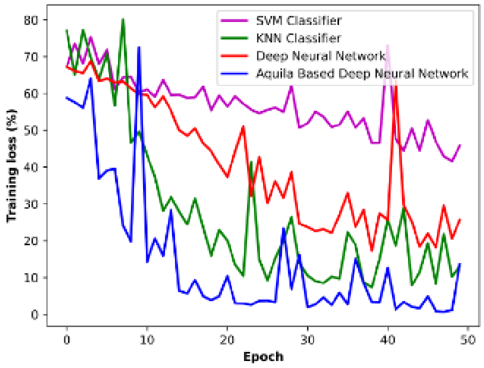


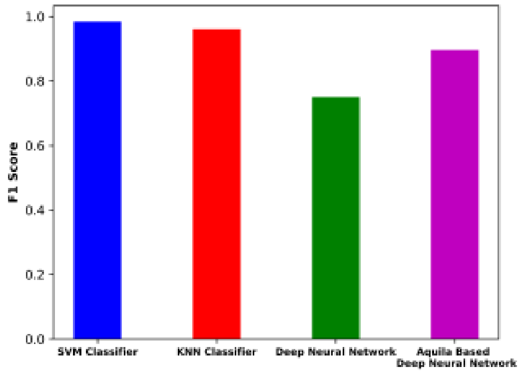
(c)



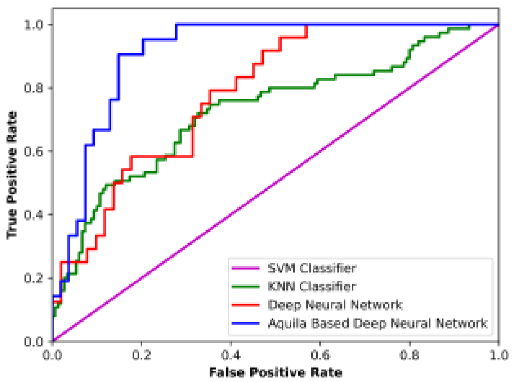
(d)

Fig 4. Comparative analysis, (a) training accuracy, (b) training loss, (c) testing accuracy, and (d) testing loss

The comparative analysis in terms of F1 score and ROC curve are depicted in figure 5. The F1 score of the methods, such as SVM, K-NN, DNN, and the proposed Aquila-DNN are 0.984, 0.961, 0.75, and 0.896, respectively as depicted in figure 5a. Figure 5b shows the ROC curve depicting the relation between TPR and FPR. When the TPR is 0.0556, the FPR is 0.381 when using the SVM classifier. When the TPR is 0.1373, the FPR is 0.4167 when using the K-NN classifier. When the TPR is 0.3333, the FPR is 0.2133 when using the DNN classifier. When the TPR is 0.1176, the FPR is 0.1176 when using the DNN classifier.



(a)



(b)

Fig. 5 Comparative analysis, (a) F1 Score, and (b) ROC curve

4.6. Comparative discussion

The comparative discussion of the techniques involved in classification of the COVID-19 cases is tabulated in table 3.

Table 3. Comparative discussion

Metrics	Methods			
	SVM	K-NN	DNN	Aquila-DNN
Training accuracy (%)	83.2	93.9	94.1	99.7
Testing accuracy (%)	84.4156	92.4026	90.9091	95.4545
Training loss (%)	37.8824	7.8836	15.3930	1.0811
Testing loss (%)	45.7367	13.1064	25.6678	13.6792
F1 Score	0.984	0.961	0.750	0.896

Hence, from the analysis, it is clear that the Aquila-DNN strategy outperforms the conventional methods in terms of accuracy, loss, and F1 score.

5. Conclusion

This paper proposes an automatic classification strategy for the classification of COVID-19 cases with the chest image data collected through the Wireless sensor networks (WSN). The cluster head (CH) selection based on the level of energy assists in the efficient transfer of data through the WSN. The chest image data is processed in such a way to extract the significant features that enhances the performance of the proposed Aquila-based Deep Neural network (DNN) classifier. The accuracy of Aquila-DNN strategy is increased with the tuning of the DNN weight parameters using the Aquila Optimizer (AO) algorithm that also helps in the enhanced convergence of the proposed method of COVID-19 case classification. The effectiveness of strategy is analyzed based on the performance indices, such as accuracy, ROC curve, and the F1 measure. The training accuracy of 99.7% and the testing accuracy of 99.4545% are achieved using the proposed classification model that shows the effectiveness of Aquila-DNN method in classification. In future, ensemble classifier will be formulated to further enhance the classification performance of proposed model.

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