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RESEARCH ARTICLE - ENGINEERING

CT-Scan Method-based Artificial Neural Network for Diagnosis of COVID-19

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Abstract

The Covid-19 epidemic appeared suddenly, with a rapid start and leaping steps, declaring a threat to global health where it was the beginnings of its upbringing in Wuhan, China. Where the World Health Organization announced after confirming the results of human infections in December 2019 that it hurts all aspects of life in general and human health in particular. Therefore, it requires addressing such an epidemic quickly and with tight steps to avoid aggravating the situation, especially the lack of appropriate treatment. The necessity necessitated the use of quarantine for the injured and social distancing, in addition to the use of preventive measures such as masks, hand sterilization, non-contact, and leaving a safe distance. This paper aims to use an ANN algorithm based on CT and some laboratory and clinical parameters to determine whether a person is infected with Covid-19 or not. The results showed that two hidden layers were chosen for the ANN algorithm, where the first hidden layer was installed with ten nodes, while the second hidden layer was selected with five nodes once, ten nodes again, fifteen nodes, and twenty nodes. The results showed the best two hidden layers 10-20 nodes, and the accuracy was 99.43%.

Publisher : Middle Technical University

Keywords: ANN; Backpropagation Neural Network; COVID-19; CT-Scan; D-Dimer Diagnosis; Heart Rate; SpO_2; X-ray.

1. Introduction

Covid-19 has swept the world quickly and was ranked fifth after the influenza pandemic recorded in 1981. The first infections were recorded in Wuhan, China, according to the World Health Organization (WHO) statistics, which it announced on December 31, 2019 [1]. As the Coronavirus infects humans and animals, it marks the beginning of the virus spreading to all countries of the world in a short and quick time due to its virulence. The clinical observations of this epidemic's symptoms were the patient's high temperature (fever) and the accompanying headache, coughing, thinness, and difficulty breathing, resulting in pneumonia [2]. It has been observed that the size of the Coronavirus is rather average because it contains a sizeable viral genome known as Ribonucleic Acid (RNA). Since the Coronavirus infects animals, including birds, bats are one of the largest hosts of viral genotypes of this disease, and this, in turn, is an important point, as it represents a link for the transmission of infection to humans, and this is either by eating infected bats or transmission of infection to food that people eat. The latest statistics of the World Health Organization, on April 29, 2022, recorded approximately (510,270,667) people infected with the Coronavirus with certainty, including (6,233,526) deaths as a result of the disease. The epidemic affected all countries of the world, representing 221 countries, as it did not exclude even remote areas. Since the epidemic spread and is considered a global pandemic, it has been accompanied by many challenges for humans, as it disturbingly disturbed the world, leading to economic, political, and social crises.

As a result of the confusion caused by the Coronavirus, specialists worked on studying this problem, knowing the merits of the infection, determining its initial stages, and isolating the infected within the scope of quarantine to limit the transmission of infection to other people. In the contexts in which he works to know whether the person is infected or not infected with the Coronavirus, he worked on the use of two mechanisms in the detection of Covid-19, and the first was the DNA test, the antigen test, and the antibody test, in addition to the point of care. The second mechanism included both x-rays and computerized tomography to detect the injury. The first mechanism was laboratory and laboratory procedures applied to the affected person by taking a swab of sputum, throat, and deep airway [3]. It is followed by a real-time polymerase chain reaction (RT-PCR) diagnostic procedure, which leads to the knowledge of viral nucleotides.

Moreover, recent reports indicate that the strength of the diagnosis of COVID-19 in terms of sensitivity is 71% in RT-PCR, while in computed tomography, it reaches 98% [4]. As for the other mechanism in diagnosing the disease, it was represented in the radiological methods, which are x-rays and computerized tomography, which is determined through the patient's lung, for medical diagnosis of infection with Covid-19, as it represented a high diagnosis rate in the management of patients who confirmed or suspected infection.

Diseases related to the respiratory system are optimally diagnosed by x-rays or computed tomography, as well as knowledge of diseases similar in terms of infection [4]. Therefore, radiological methods are more accurate than laboratory tests to determine infection with the Coronavirus, as it is an approved method for detecting and distinguishing Covid-19 disease [5].

Nomenclature& Symbols			
RNA	Ribonucleic Acid	RT-PCR	Real-Time Polymerase Chain Reaction
CNN	Convolution Neural Network	CAP	Community-Acquired Pneumonia
SpO2	Blood Oxygen Saturation	RGB	Red Blue Green
CT	Computerized Tomography	ANN	Artificial Neural Network
MSE	Mean Squared Error	MAE	Mean Absolute Error
RMSE	Root Mean Squared Error	R^2	Correlation Coefficient
LR	Learning Rate	DNN	Deep Neural Network
Tp	True Positive	Tn	True Negative
Fp	False Positive	Fn	False Negative
KNN	K-Nearest Neighbor	SVM	Support Vector Machine
DT	Decision Tree	DL	Deep Learning
PSO	Particle Swarm Optimization	WHO	World Health Organization
DNA	Deoxyribonucleic Acid	GP	Generalized Pneumonia
EBT	Ensemble Of Bagged Tree	SpO_2	Oxygen Saturation
D-dimer	Degradation Product Of Cross-Linked Fibrin		

Computed tomography has been characterized by high sensitivity in diagnosing the disease and is considered an essential focus for detecting and predicting the disease by distinguishing the different patterns that depend on ground glazing, merging, and uniting alone [6]. The increase in the cases of the injured has exacerbated the health situation, as it caused pressure on the health staff, which in turn puts them in a critical condition in the knowledge of the injury, which puts them in a state of physical fatigue and mental exhaustion. This negatively affects giving the correct result in the diagnosis. However, the use of artificial intelligence in the treatment of diagnosis and decision-making is an essential and vital issue for health care points, which in turn helps to manage the crisis that accompanies the results of infection with Covid-19, in terms of accuracy of diagnosis and speed of decision-making, in addition to limiting the expansion of the diseased area [7].

Many researchers have worked on artificial intelligence models to detect infection with the Coronavirus, using X-rays or computed tomography, As shown in Table 2. Z. Yang et al. [8] worked on a 3D-ResNet algorithm based on computed tomography to detect and differentiate patients with COVID-19 and community-acquired pneumonia (CAP). The results showed an accuracy of 88.8%. P. Dutta et al. [9] suggested working on the (Inception V3) learning transfer model and the Deep Neural Network (DNN) to accurately and quickly detect infection with the Coronavirus, relying on the use of computerized tomography, which gave results with an accuracy of 84%. P. Afshar et al. [10] suggested working on the use of clinical data with the tomography of patients, where they designed capsule networks based on CNN, in addition to using the Random Forest Classifier to decide between both community-acquired pneumonia (CAP) and COVID-19, where the accuracy of the results showed up to 90.8 %. R. Wang et al. [11] proposed a deep learning algorithm to build an (Efficient-Net) model, where patients' data consisting of computed tomography was used, where the results of the proposed model for predicting risks gave an accuracy of 83.3%. M. Pourhomayoun and M. Shakibi [12] proposed a model of multiple algorithms (SVM, DT, KNN, Logistic Regression, Random Forest, and ANN) to work on the dataset of laboratory health, demographic as well as the psychological state of the patient. It gave results with an accuracy of 89.98% for the proposed model. C. Liu et al. [13] suggested working on a set of algorithms (Ensemble of Bagged Tree (EBT), KNN, SVM, Logistic Regression, and DT) to detect COVID-19 and distinguish it from generalized pneumonia (GP). The EBT model gave the best results, with an accuracy of 94.16%. Z. Yu et al. [14] used computed tomography for patients to detect COVID-19, as they suggested working on multiple models of artificial intelligence such as (DenseNet-201, ResNet-101, ResNet-50, and Inception-V3), taking advantage of the classification of infection based on classifiers (linear discriminant, KNN, Cubic SVM, Adaboost DT, and Linear SVM). The proposed model gave an accuracy of 95.34%.

This paper aims to accurately diagnose the Covid-19 disease using a backpropagation feed-forward neural network. The patients' physiological and laboratory parameters and images from CT scans were used as input to the ANN, collected from 500 patients, and the patient's status (Positive or Negative) as the output of ANN. Two hidden layers were considered to improve the diagnosis accuracy. The first hidden layer includes ten neurons, while the neurons were tuned in the second hidden layer to obtain minimum error or high accuracy of Covid-19 diagnosis. The main contribution of this article includes the development of a multi-layer ANN model to detect and distinguish people infected with COVID-19 based on CT scans and physiological and laboratory parameters of the patients. The researchers did not include all parameters (i.e., physiological and laboratory and CT-scan images) in their research works. Some adopted CT-scan only, while others used physiological and laboratory parameters. Therefore, our work differs from the previous study by including all the parameters above to diagnose the patients infected with Covid-19 accurately.

The rest of this paper is structured as follows. Section 2 introduces materials and methods, including dataset collection, artificial neural network, and ANN processing. Section 3 presents the performance evaluation. Results and discussion are given in Section 4. Comparison results with previous articles were highlighted in Section 5. Finally, the conclusion is provided in Section 6.

2. Materials and Methods

In this section, we first describe how we collect the patients' data, containing physiological and laboratory parameters and CT scans from Hospitals. We introduce the adopted ANN topology and provide the performance metric for evaluating the operation of ANN in terms of the mean square error (MSE). Then, we divide the dataset for training, testing, and validation of ANN.

2.1. Dataset Collection

Data were collected from four hospitals: Al-Sadr Teaching Hospital, Al-Hakim Hospital, Ramadi Teaching Hospital for Women and Children, and Ramadi General Hospital in Iraq. The number of patient data was about 500, including those infected with Covid-19 and suspected of infection. The data were classified into laboratory results (D-dimer)[15], physiological parameters such as (SpO2, temperature, and heart rate), and computed tomography of the patient, as shown in Fig. 1. The parameters of patients are related to physiological and laboratory parameters.

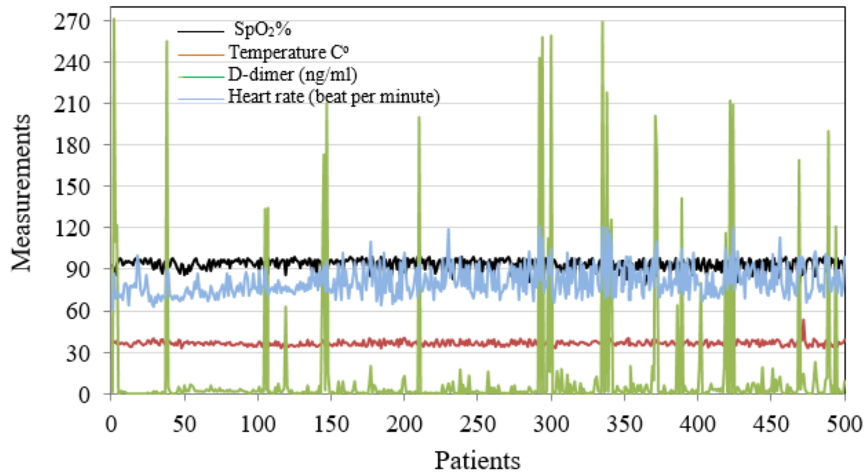


Fig. 1. Patients' physiological and laboratory parameters readings

Twenty readings were taken from the computed tomography of the patient's lung, that is, ten readings from the right lung and ten from the left lung focused on the areas of injury to the inner lung wall and its surroundings. Inside the lung, each patient had ten samples combined, bringing the total samples are 5000.
Fig. 2 shows the parameters for each patient, including 20 readings of the patient's lung, ten readings for the right lung, and ten for the left side. Each reading represents one pixel's value and ranges from 0 to 255, where 0 represents black and 255 represents white.

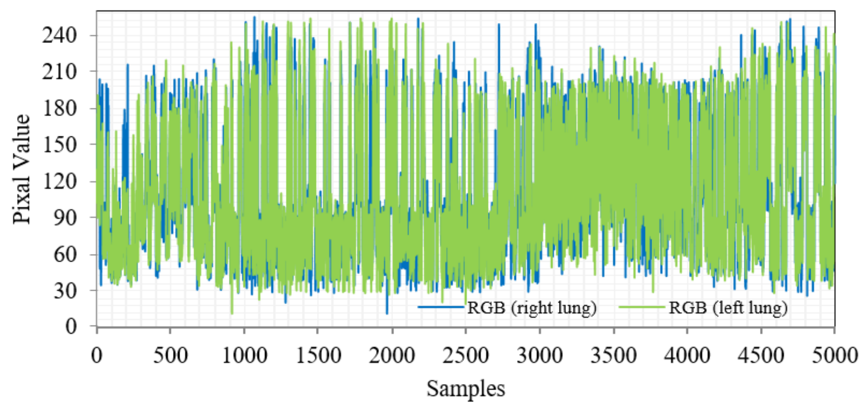


Fig. 2. The readings of the patient's lung CT parameters

2.2. Artificial Neural Network

The features were obtained using (ANN). In the medical field, this network helps in achieving rapid disease identification. The work was done on a multi-layer neural network for the feed-forward [16]. The proposed model consists of an input layer, two hidden layers, and an output layer. The data is entered into the (ANN) algorithm within the input layer with ten parameters for each sample, where the backpropagation training algorithm is used, which is used to modify the weights and threshold parameters. In the hidden layer, according to the number of nodes, the parameters are multiplied by an initial weight value, and the bias value is added. Then the process is repeated in the second hidden layer after the resulting weights from the first hidden layer have been modified. Finally, showing the final results, depending on the lowest value of the MSE [17], and repeating the process under the same period until the best results are obtained. Fig. 3 shows the proposed network architecture for COVID-19 detection.

2.3. ANN processing

The Backpropagation algorithm consists of an input layer, two hidden layers, and an output layer. The two hidden layers have n nodes plus a bias, such that the biases W and V give the behaviour of the weights. The Backpropagation algorithm is carried out through three stages: training the input patterns within the feedforward step, performing a backpropagation for the resulting associated errors, and then updating the resulting weights. In the stages of the training process, each input value is calculated within each hidden layer to obtain a final output as the training process compares the results of the previous steps of calculations during training and compares them with the main target. Here, an error is calculated to carry out an optimization mechanism for the factors to obtain the lowest value. Factors make weight-related challenges within the input and output layers [18].
Matlab program was used to implement the proposed ANN algorithm. The data set for patients were divided into three sections, 70% for training, 15% for testing, and 15% for validation [19]. After preparing the data, it is presented as a simple problem that requires the prediction of referrals and is represented as follows xi, for $i = 1,2, \ldots,10$. where (xi) is the input vector of parameters to the input layer in the training network of the algorithm. (i) represents the number of parameters for each patient.

The ANN algorithm has been implemented in several attempts to obtain results and compare them to reach the best number of nodes in each hidden layer, which gives speed and strength to the results. The number of nodes in the first hidden layer was fixed with ten nodes, in addition to using the learning rate value (0.5) [20]. For the second hidden layer, the number of nodes (5) was used, then (10) nodes, (15) nodes, and finally (20) nodes. Moreover, based on patient data is processed into the network after being randomly arranged.

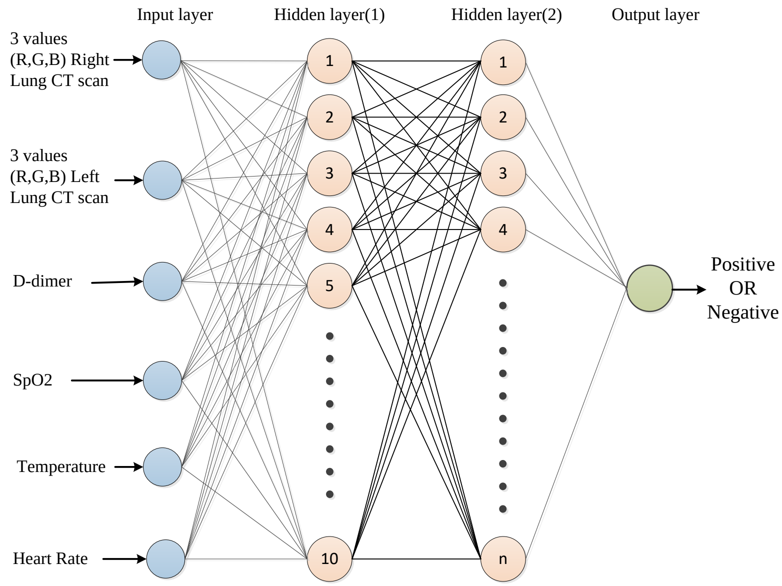


Fig. 3. ANN based on a backpropagation algorithm for training data

3. Performance Evaluation

The target is set for grids 1 and 0, representing the output. By implementing ANN, the Mean Absolute Error (MAE) according to Equation (1), the Mean Squared Error (MSE) according to Equation (2), the Root Mean Square Error (RMSE) according to Equation (3), and the Correlation Coefficient (R^2) according to Equation (4) [21] Between the actual value and the target value of each network, the best performance of the ANN algorithm is obtained by the relationship between the MSE and the number of epochs, which is 1000, so the number of epochs is the number of times the network has been trained. Fig. 4 below shows a flowchart of how the ANN algorithm works.

The database used to provide ANN with both infected and non-Covid-19 patients is 500 patients. The result of network training, testing, and validation is the accuracy of infection detection. By providing the ANN algorithm with the database, as shown in Figs. 1 and 2, and depending on the structure of the neural network or the number of nodes in the first and second hidden layer, the higher the number of nodes, the lower the error rate of the neural network. As can be seen in Fig. 4, which highlights the Means Square Error (MSE) results from the training, testing, and validation process for the hidden layers (10 - 5), (10 - 10), (10 - 15), and finally (10 - 20), noting that The number of epochs is 1,000 and the threshold for reaching the goal is 1×10^{-4} with a consistent learning rate of 0.5 [22].

$$MAE=\frac{1}{n}\sum_{i=1}^{n}(ki-\widehat{ki}) \quad (1)$$

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(ki-\widehat{ki})^2 \quad (2)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(ki-\widehat{ki})^2} \quad (3)$$

$$R^2=1-\frac{\sum_{i=1}^{n}(ki-\widehat{ki})^2}{\sum_{i=1}^{n}(ki-\hat{k})^2} \quad (4)$$

where: ki: is the actual target, $\widehat{ki}$: is the expected output, $\hat{k}$: expected the mean of ki, n: the expected number of adopted samples.

Fig. 4 illustrates the flow chart of the ANN algorithm and shows the program execution steps. It starts by setting up the database configuration according to the parameter classes mentioned in Section 2.1 Figs. 1 and 2. In addition to fixing the number of nodes in the first hidden layer, which is ten nodes, and then fixing the number of nodes in the second hidden layer with five nodes, after the end of the general implementation of the algorithm and fixing the results. Then we return the ball to the second hidden layer by changing the number of nodes to 10, 15, and 20 nodes and fixing the results of each implementation. Determine the learning rate of 0.5 [20], the error goal as 1×10^{-4} [23], and the number of epochs as 1000. The algorithm stops when the target value is reached, considering that it achieved the lowest value of the error goal. In light of this, the Performance Evaluation is calculated to obtain the results from all the changes that were made, and as shown in Table 1, the results of the ANN algorithm, and according to the results that appeared, the structure of the ANN algorithm is determined, which achieves the best results in accuracy for detecting Covid-19.

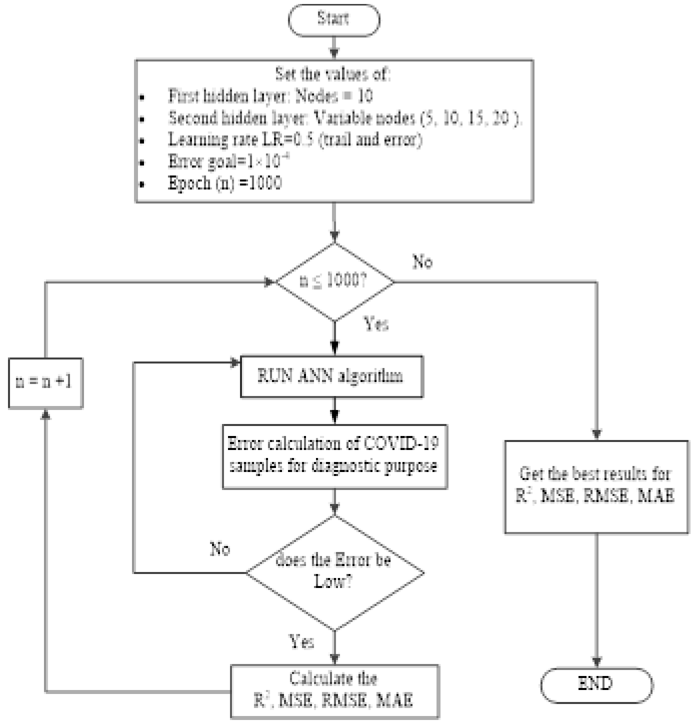


Fig. 4 Flow chart of ANN Algorithm

4. Results and Discussion

To implement the ANN injury detection algorithm, a laptop with a 6th Gen Core i7 processor, 2.60 GHz, 10240 MB RAM, discrete graphics card NVIDIA 4095MB, and 250GB SSD was used. The version of the software used is MATLAB R2021a. The results of performance measures for ANN showed at 1000 training epochs (10-5) nodes, (10-10) nodes, (10-15) nodes, and finally (10-20) nodes. Where the results of the performance of MSE are (9.33×10^{-5}), (8.48×10^{-5}), (2.74×10^{-5}), and (9.01×10^{-5}), respectively, as shown in Fig. 5 (a). The results of performance measures for ANN showed at 1000 testing epochs (10-5) nodes, (10-10) nodes, (10-15) nodes, and finally (10-20) nodes. Where the results of the performance of MSE are (0.0076), (0.0056), (0.008), and (0.0069), respectively, as shown in Fig. 5(b). The results of performance measures for ANN showed at 1000 validation epochs (10-5) nodes, (10-10) nodes, (10-15) nodes, and finally (10-20) nodes. Where the results of the performance of MSE are (0.0062), (0.0037), (0.0037), and (0.0019), respectively, as shown in Fig. 5(c).

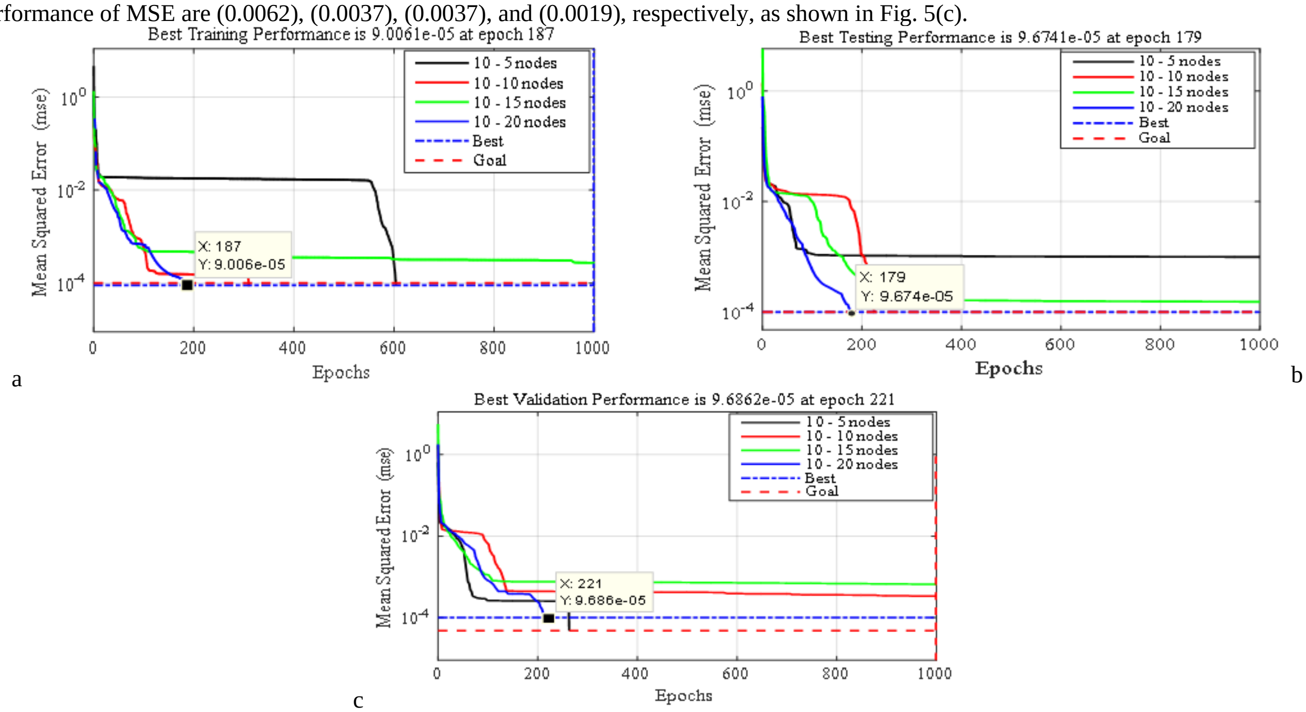


Fig. 5 Performance of different nodes of ANN for (a) training, (b) testing, and (c) validation

In light of the results that appeared through MSE, for the training, testing, and validation process for (10-5) nodes, (10-10) nodes, (10-15) nodes, and (10-20) nodes. The best ANN structure that gives the best performance results is (10-20) nodes. So we show the rest of the results related to the Correlation coefficient (R^2) and error curve for the process of training, testing, and validation of the nodes (10-20). For the training, testing, and validation correlation coefficient (R^2) of the ANN, a plot can be shown highlighting the exploration of the discrepancy between the target (X-axis) and the expected value generated by the ANN (Y-axis). It gave training, testing, and validation for (10-20) knots, showing the results (0.99982), (0.9998), and (0.9998) as shown in Fig. 6, respectively.

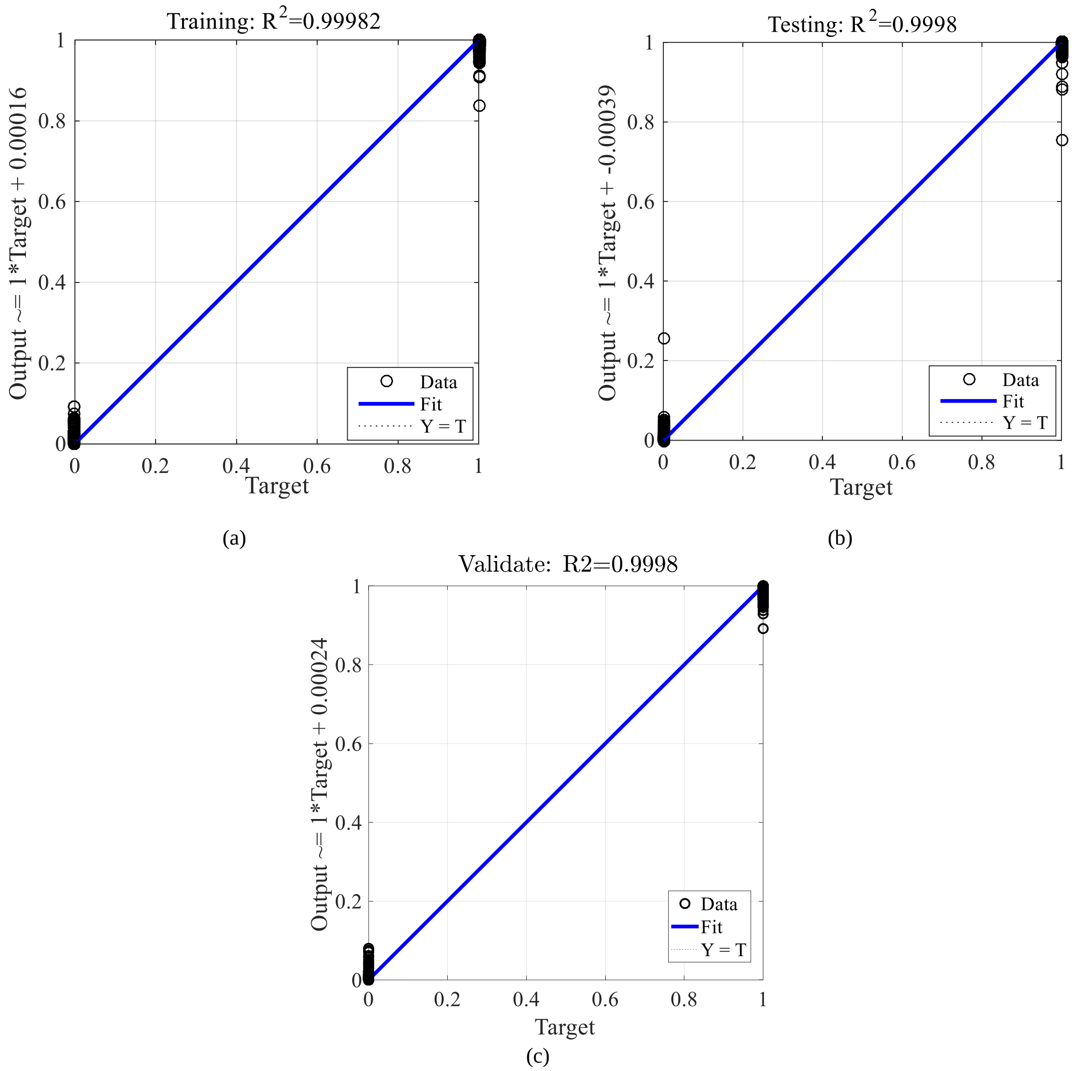
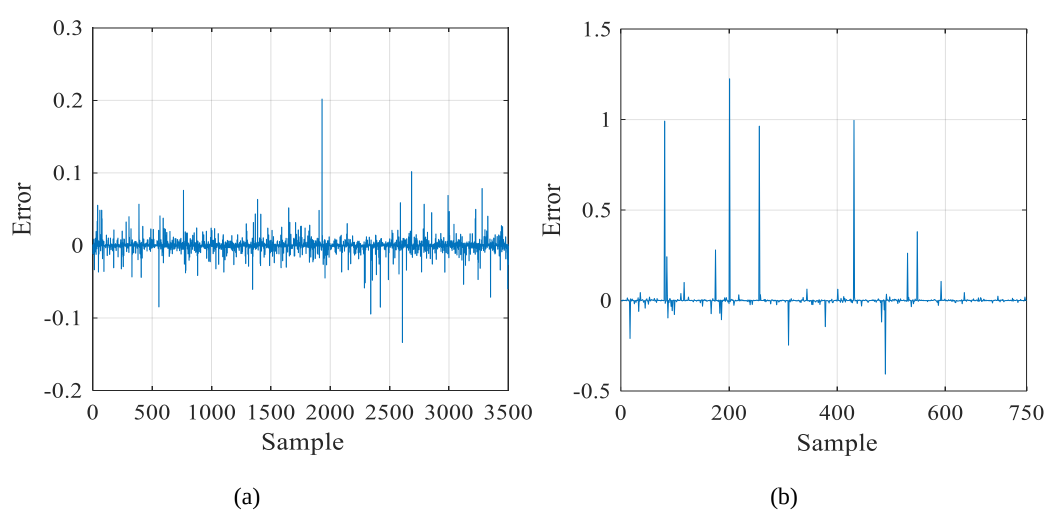
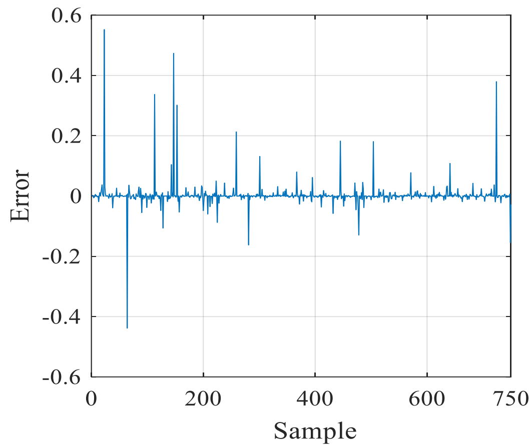


Fig. 6. The correlation coefficient of ANN at 10-20 nodes for (a) training, (b) testing, and (c) validation.

In Fig. 7, the error curve is shown for patient samples, where the error variance was for training (10-20) nodes and between (0.20 to -0.13). Testing (10-20) nodes, where it was between (1.22 to -0.4), validation (10-20) nodes, where it was between (0.55 to -0.43).





(c)

Fig. 7. ANN error when 10-20 nodes are adopted for (a) training, (b) testing, and (c) validation

After the results were collected through training, testing, and validation of the algorithm, as shown in Table 1. The address categories (MAE, MSE, RMSE, and R^2) and the number of nodes in each first and second hidden layer.

In light of the results in Table 1. The accuracy of the proposed system can be obtained through the following Equation [24]:

$$\text{Accuracy}=\frac{(Tp+Tn)}{(Tp+Fp+Tn+Fn)}\times 100\% \quad (5)$$

where true positive (Tp) is the number of confirmed cases of infection, and False Positive (Fp) is the number of cases similar to those infected with the disease but not infected. True Negative (Tn) is the number of uninfected cases, and False Negative (Fn) is the number of infected cases, but, similarly, they are not infected.

Table 1. ANN System Training, Testing, and Validation Results

Number of Nodes in 2 hidden layers		MAE	MSE	RMSE	R^2	Accuracy(%)
Training	10 nodes - 5 nodes	0.0029	9.33×10^{-5}	0.0097	0.99981	99.97
	10 nodes - 10 nodes	0.0027	8.48×10^{-5}	0.0092	0.99983	100
	10 nodes - 15 nodes	0.0049	2.74×10^{-5}	0.0166	0.99944	100
	10 nodes - 20 nodes	0.0042	9.01×10^{-5}	0.0095	0.99982	100
Testing	10 nodes - 5 nodes	0.0137	0.0076	0.087	0.99797	98.93
	10 nodes - 10 nodes	0.0122	0.0056	0.0751	0.9998	99.06
	10 nodes - 15 nodes	0.0158	0.008	0.0892	0.99969	99.33
	10 nodes - 20 nodes	0.0134	0.0069	0.0831	0.9998	99.06
validate	10 nodes - 5 nodes	0.0108	0.0062	0.0786	0.9999	99.41
	10 nodes - 10 nodes	0.0111	0.0037	0.0611	0.99931	99.36
	10 nodes - 15 nodes	0.0209	3.70×10^{-3}	0.0611	0.99866	98.93
	10 nodes - 20 nodes	0.011	0.0019	0.0433	0.9998	99.43

The parameters of the accuracy Equation were fed by relying on the validation results for the ANN system since injury and non-injury were specified with (1 and 0), respectively, for the actual database. However, the expected results were validated from the network training output. Since the data issued by it ranges from 1.09 to -0.32 for the (10-5) nodes, 1.22 to -0.38 for the (10-10) nodes, 1.2 to -0.22 for the (10-15) nodes, and 1.29 to -0.30 for the (10-20) nodes. A threshold was set to distinguish the infected from the uninfected with a value of 0.8. The expected data can be separated and rounded to limits confined between two values: either one is indicated for infection or 0 is indicated as not injured. By comparing the actual outputs of the database with the results of the expected ANN outputs within the validation samples, the actual infection cases are calculated with what the (expected) validation results showed that are similar to the result, summed as a numerical value, and substituted in Tp. The number of infected cases is calculated and compared with the (expected) validation results that match with parameters but disagree with the output. Sum up it as an integer and replace it in Fp.

As for the actual outputs of the uninfected samples, they are compared with the expected results and collect similar ones as a numerical value and substitute their value in Tn, as well as for the actual outputs of the validation samples for uninfected patients. They are compared with the algorithm results for the expected outputs in case of non-conformity as they indicate the presence of an infection. However, its samples indicate otherwise in the original, so it sums the number of outputs that do not agree with each other as a numerical value and substitutes its value in Fn. The accuracy results of the validation set of the ANN algorithm after applying equation (5) were shown in light of what has been explained above. The best result was based on validation, which showed an accuracy of up to (99.43%) in the nodes (10 - 20) In terms of distinguishing the infected person from the uninfected. In addition, the performance evaluation results showed that the nodes (10-20) were the best compared to the other nodes.

5. Comparison Results

As explained in the experiment results and discussion section, the multi-layer ANN algorithm was used to solve the problem of detecting COVID-19 patients based on a set of parameters (see Figs. 1 and 2). A trial and error method was carried out for selecting the number of nodes in the second hidden layer while fixing the number of nodes in the first hidden layer to reduce the excessive training time of the network of the training, testing, and validation process. To reach a measure of performance provided by the proposed algorithm, the accuracy of the algorithm for the number of nodes in each layer was highlighted (see Table 1), as the number of nodes (10-20) showed the best results in terms of accuracy, MSA, and RMSA depending on the validation of the algorithm, whose results that appeared with the previous work can be compared in Table 2, where this algorithm contributed to showing better results for the detection of COVID-19 and reducing the rate of error in predicting injury.

Table 2. Comparison of different AI algorithms used to detect and distinguish COVID-19

REF/Year	Patients/Images	Adopted algorithm	Accuracy (%)
[8]/2021	171 patients	3D-ResNet	88.8
[9]/2021	558 images	CNN (DNN + Inception -V3)	84
[10]/2021	312 patients/ 23494 images	hybrid deep learning model (CT-CAPS)	90.8
[11]/2021	1051 patients	DL(Efficient-Net)	83.3
[12]/2021	2,977,382 patients	KNN, Random Forest, SVM, Logistic Regression, DT, and ANN	89.98
[13]/2020	100 patients	SVM, DT, KNN, and logistic regression	94.16
[14]/2020	729 patients	DT,[cubic SVM], linear discriminant, KNN, and [linear SVM]	95.34
2022	**500 patients**	**Proposed ANN**	**99.43%**

6. Conclusion

From what was presented in the results of the experiment and discussion, it can be concluded about ANN, specifically the backpropagation neural network, in terms of its performance, that the multiplicity of hidden layers in addition to the number of nodes they contain in the case of applying the particle swarm optimization algorithm -PSO will give better performance to predict the best number of nodes in Each layer is hidden in addition to giving the best value for the learning rate. This will save the computational time of the proposed system, in addition to the speed of implementation and showing the results. This will reduce the error rate in predicting the condition of those infected with Covid-19. In addition, if the data set is for non-Covid-19 patients, that is, diseases that affect the respiratory system, especially the lung, the proposed algorithm, combined with deep learning algorithms, can improve the readability of results and distinguish between multiple pneumonia diseases, including COVID-19 in the future.

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