

# COVID-19 Classification based on Neutrosophic Set Transfer Learning Approach



Rebin Abdulkareem Hamaamin<sup>1</sup>, Shakhawan Hares Wady<sup>1</sup>, Ali Wahab Kareem Sangawi<sup>2</sup>

<sup>1</sup>Applied Computer, College of Medicals and Applied Sciences, Charmo University, Chamchamal, Sulaimani, KRG, Iraq,

<sup>2</sup>General Science, College of Education and Language, Charmo University, Chamchamal, Sulaimani, KRG, Iraq

## ABSTRACT

The COVID-19 virus has a significant impact on individuals around the globe. The early diagnosis of this infectious disease is critical to preventing its global and local spread. In general, scientists have tested numerous ways and methods to detect people and analyze the virus. Interestingly, one of the methods used for COVID-19 diagnosis is X-rays that recognize whether the person is infected or not. Furthermore, the researchers attempted to use deep learning approaches that yielded quicker and more accurate results. This paper used the ResNet-50 module based on the Neutrosophic (NS) domain to diagnose COVID patients over a balanced database collected from a COVID-19 radiography database. The method is a future work of the N. E. M. Khalifa *et al.*'s method for NS set significance on deep transfer learning. True (T), False (F), and Indeterminate (I) membership sets were used to define chest X-ray images in the NS domain. Experimental results confirmed that the proposed approach achieved a 98.05% accuracy rate outperforming the accuracy value acquired from previously conducted studies within the same database.

**Index Terms:** COVID-19, Chest X-ray, Neutrosophic set, ResNet-50, Classification

## 1. INTRODUCTION

COVID-19 is a respiratory disease caused by SARS-CoV-2 coronaviruses derive their name from their spherical viruses, which had a shell and a surface projection similar to the solar corona [1]. Unfortunately, the number of deaths from COVID-19 is increasing daily, which has led scientists to work tirelessly to develop a tool to diagnose all types of COVID. There are several ways to diagnose the disease, including blood tests and chest X-ray (CXR) images [2]. The two most popular imaging studies for diagnosing and managing COVID-19 patients are the CXR and computed tomography (CT) scan images. Chest radiography and CT scans, on the other hand, are widely available at most medical centers and

typically interpreted with a faster turnaround time than the SARS-CoV-2 laboratory testing. The use of CXR images in the monitoring and examination of numerous lung disorders including tuberculosis, infiltration, atelectasis, pneumonia, and hernia has been known. COVID-19 predominantly affects the respiratory system, resulting in severe pneumonia and acute respiratory distress syndrome in extreme cases. For the most part, X-ray images of the chest are used to diagnose COVID-19-infected patients [3]. Therefore, there are many researches on the diagnosis of COVID-19 using CXR images.

One of the modern methods used in the diagnosis of COVID-19 is the use of deep learning (DL) techniques, which is deep neural network learning. The DL approach has the advantage of automatically extracting features from training data and classifying them more accurately than other traditional methodologies [4]. ResNet, abbreviation for Residual Networks, is a conventional neural network that acts as a foundation for many image processing applications. ResNet's fundamental achievement was that it enabled us to train extraordinarily deep neural networks

### Access this article online

DOI: 10.21928/uhdjst.v6n2y2022.pp11-18

E-ISSN: 2521-4217

P-ISSN: 2521-4209

Copyright © 2022 Hamaamin, *et al.* This is an open access article distributed under the Creative Commons Attribution Non-Commercial No Derivatives License 4.0 (CC BY-NC-ND 4.0)

**Corresponding author's e-mail:** Rebin Abdulkareem Hamaamin, Applied Computer, College of Medicals and Applied Sciences, Charmo University, Chamchamal, Sulaimani, KRG, Iraq. E-mail: rebin.abdulkarim@charmouniversity.org

Received: 01-06-2022

Accepted: 17-07-2022

Published: 01-08-2022

with 150+ layers. ResNet-50 architecture is a well-known convolutional neural network (CNN) DL model with 50 layers for image classification [5]. All CXR images are in the spital domain, then transformed into a new domain called the Neutrosophic (NS) domain. The NS includes crisp set, NS graph theory, NS fuzzy set, NS image, and NS topology built on the foundation of NS. The use of these parts on image parts is called advanced image preprocessing, which entails image transformation into the NS domain, The NS domain comprises of three sorts of images, and they are the True (T) images, Indeterminacy (I) images, and Falsity (F) images [6]. All three membership (True, False, and Indeterminate) images were generated in this study.

The identification of COVID-19 as a classification task is addressed in this study using a system based on ResNet-50 architecture in the NS domain. The key contribution of this paper is to analyze the effectiveness of utilizing NS sets based on ResNet-50 architecture using huge database images to improve the overall accuracy and thereby reduce the misclassification error rate. The remainder of the paper is organized as follows. Section 2 presents a review of related research, a complete proposed framework for the detection of COVID-19, including sections such as a database description, image in the NS domain, and ResNet-50 model depicted in Section 3. Section 4 discusses the experimental results and discussions and comparing them with the existing approaches. Finally, Section 5 provides the conclusion of the work.

## 2. RELATED WORK

Over the past 2 years, numerous studies on COVID-19 infection diagnosis and detection have been conducted. For instance, Lawton [7] proposed COVID-19 detection schema from CT lung scans using transfer learning architectures Standard Histogram Equalization and Contrast Limited Adaptive Histogram Equalization. Five pre-trained CNN-based models (Inception-ResNetV2, InceptionV3, ResNet-50, ResNet101, and ResNet152) for detecting coronavirus pneumonia-infected patients using CXR radiographs were recommended in Narin *et al.* [8] Three separate binary classifications comprising four classes (COVID-19, normal, bacterial pneumonia, and viral pneumonia) were generated applying five-fold cross-validation. Ilyas *et al.* [9] suggested a real-time rule-based Fuzzy Logic Classifier for COVID-19 detection. The suggested methodology collects real-time symptom data from users through an Internet of Things platform to identify symptomatic and asymptomatic

COVID-19 patients. Sharmila and Florinabel [10] attempted to classify COVID-19 afflicted individuals using CXR scans utilizing new model of CNN and DCGANs. Hira *et al.* [11] classified COVID-19 patients utilizing nine transfer learning methods. In comparison to other approaches, the ResNet-50 produced the best COVID-19 detection results for binary and multi-classes, according to the outcomes of the experiments.

Saiz and Barandiaran [12] proposed a new testing methodology to determine whether a patient has been infected by the COVID-19 virus using the SDD300 model. The deep feature plus SVM-based procedure was proposed in Singh *et al.* [13] for identifying coronavirus infected patients by applying CXR images. SVM was utilized for classification rather than DL-based classifiers, which require a large database for training and validation. Helwan *et al.* [14] introduced a transfer learning approach to diagnose patients who were positive for COVID-19 and distinguish them from healthy patients using ResNet-18, ResNet-50, and DenseNet-201. For this purpose, 2617 chest CT images of non-COVID-19 and COVID-19 were experimented. Alruwaili *et al.* [15] proposed an improved Inception-ResNetV2 DL model for accurately diagnosing chest CXR images. A Grad-CAM technique was also computed to improve the visibility of infected lung parts in CXR scans. Aradhya *et al.* [16] proposed a system for detecting COVID-19 from CXR scans. In the case of DL architectures, a novel idea of cluster-based one-shot learning was developed. The suggested schema was a multi-class classification system classifying images into four groups: Pneumonia virus, pneumonia bacterial, COVID-19, and typical cases. The proposed schema is built using a combination of an ensemble of Generalized Regression Neural Network and Probabilistic Neural Network classifiers.

Ji *et al.* [17] presented a COVID-19 detection approach based on image modal feature fusion. Small-sample enhancement preprocessing, including spinning, translation, and randomized transformation, was initially conducted using this methodology. Five classic pretraining models including VGG19, ResNet152, Xception, DenseNet201, and InceptionResnetV2 were utilized to extract the features from CXR images. Gaur *et al.* [18] presented an innovative methodology for preprocessing CT images and identifying COVID-19 positive and negative. The suggested approach used the principle of empiric wavelet transformation for preprocessing, with the optimal elements of the image's red, green, and blue channels being learned on the presented approach. Deep and transfer learning procedures recommended by Qaid *et al.* [19] to differentiate COVID-19 cases by assessing CXR images. The designed approaches used either CNN or transfer learning

models to effectively utilize their potential or hybridize them with sophisticated ML procedures Turkoglu [20] presented a pertained CNN-based AlexNet architecture employing the transfer learning technique deployed for COVID-19 identification. The effective features generated using the relief feature selection process were classified using the SVM method at all layers of the architecture. Finally, Al-Ani and Al-Ani [21] reviewed a number of studies on the subject of COVID-19 disease based on a variety of important criteria, including the topic, the applied method, the applied database, the researcher by countries, and the search by country. The findings showed that the majority of research publications supported the claim that coronavirus attacks the human respiratory system.

The rest of this work focuses on expanding and improving the method of applying digital image processing to improve the rate of COVID-19 identification performance using CXR images. The effectiveness of the proposed approach is therefore validated based on different metrics.

### 3. MATERIAL AND METHODOLOGY

In this paper, an attempt was made to develop a system for the identification and diagnosis of COVID-19 as shown in Fig. 1. To start, all CXR images were cropped to extract only Regions of Interest (ROI) and resized in the preprocessing step. At the

second step, the RGB color input images were converted into the NS domains for all three membership subsets. Afterward, the approach divided the NS images through Resnet-50 model into training and testing set in the ratio of 80:20 and then the system runs to use Resnet-50 to classify the CXR images. Finally, the recommended system’s performance was evaluated using a variety of well-known metrics including accuracy, sensitivity, specificity, precision, F-score, and Matthews Correlation Coefficient (MCC) rates [22]. The details of the proposed method were presented in the subsequent subsections.

#### 3.1. COVID-19 Database

The structure of the database is the primary stage in any computerized technique. Therefore, a database was created based on the COVID-19 radiography database which is a publicly available database. The database consists of 21165 CXR images, of which 10,192 belong to normal, 3616 correspond to COVID-19 positive, and 6012 belong to lung opacity (non-COVID lung infection) 1345 are labeled as viral pneumonia cases. The data for this paper include 7232 CXR images (Fig. 2), 3616 of which with a positive COVID-19 diagnosis, and 3616 negatives randomly selected to create the balanced database.

#### 3.2. Preprocessing

Image preprocessing refers to the steps performed to prepare images before they are used in model training and validation. Image data preprocessing is the process of converting image

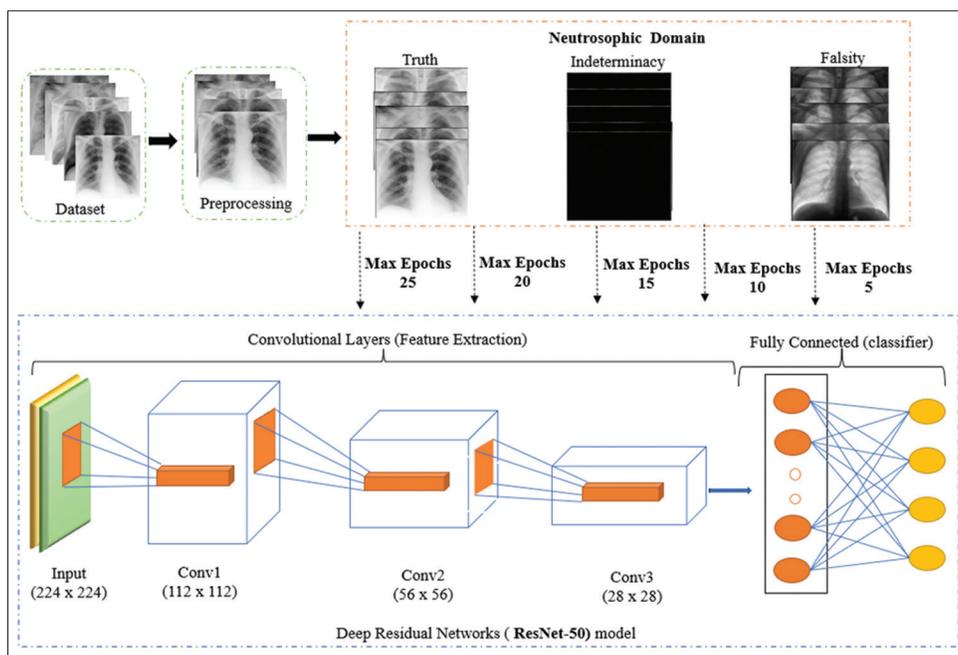


Fig. 1. General architecture of the proposed framework.

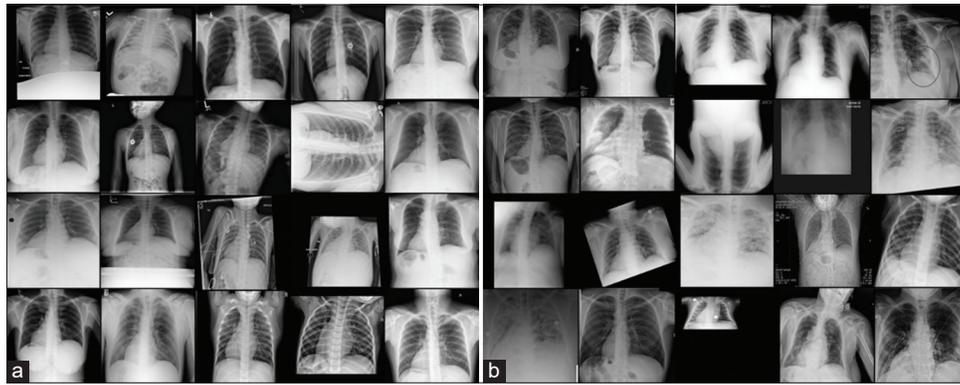


Fig. 2. Examples of CXR images: (a) COVID-19 and (b) Normal.

data into a format that machine learning algorithms can understand. It is widely used to increase the model accuracy while also minimizing its complexities. Image data are preprocessed using a variety of procedures. Therefore, in this step, the bounding box cropping approach is computed to extract the only ROI alone by removing the unwanted background from the input image. Before importing the input CXR images into the proposed framework, the cropped CXR images are resized into fixed size of 256\*256 pixels.

### 3.3. Image in the NS Domain

Neutrosophy is a field of philosophy founded in 1980 by F. Smarandache, which broadened dialectics and investigated the genesis, nature, and extent of neutralities and their interactions with various ideational spectrums. Advanced image processing includes image transformation into the NS domain that includes three areas — background subtraction for foreground objects, edge detection for boundary objects, and background detection for background objects. According to the theory of Neutrosophy, each event has a specific degree of truth (T), falsity (F), and indeterminacy (I), all of which must be taken into account separately. NS truth domain displays all the true parts of the images in percentage. At that point, the image is called an image true. Furthermore, the NS falsity membership degree presents the incorrect parts of the image and become an independent image separate from the other parts. The NS indeterminacy membership degree, which contains the least information of the original image, refers to the uncertain parts of any image [23], [24]. An  $M * N$  matrix represents the image as a mathematical object (Spatial Domain). Pixel  $P(i, j)$  in the image domain is translated into a NS domain by calculating  $PNS(i, j) = T(i, j), I(i, j), F(i, j)$  in equations (1)-(3), where  $T(i, j), I(i, j)$ , and  $F(i, j)$  are taken as probabilities [25] that pixel  $P(i, j)$  belongs to white set (object), indeterminate set, and non-white set (background), respectively (Fig. 3).

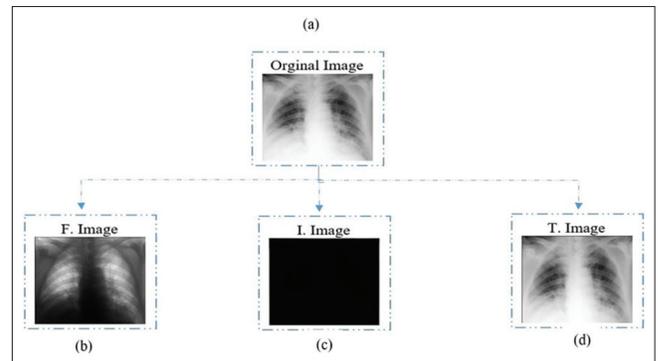


Fig. 3. Convert image from Spatial domain to NS domain: (a) Original Image (COVID-19), (b) F-domain of COVID-19 image, (c) I-domain of COVID-19 image, and (d) T-domain of COVID-19 image.

$$T(i, j) = \frac{\bar{g}(i, j) - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}} \quad (1)$$

$$I(i, j) = \frac{\delta(i, j) - \delta_{min}}{\delta_{max} - \delta_{min}} \quad (2)$$

$$F(i, j) = 1 - T(i, j) = \frac{\bar{g}_{max} - \bar{g}(i, j)}{\bar{g}_{max} - \bar{g}_{min}} \quad (3)$$

where:

- $g(i, j)$  indicates the pixel intensity value of an image.
- T, I, and F are true, indeterminacy and false sets, respectively, in NS domain.
- $\bar{g}(i, j)$  is the local mean value of  $g(i, j)$ .
- $\delta(i, j)$  is the homogeneity score of T at  $(i, j)$ , which is defined as the absolute amount of the difference between an image's intensity value  $g(i, j)$  and its local mean value  $\bar{g}(i, j)$ .

### 3.4. Deep Residual Neural Network (ResNet-50) Model

DL is a machine learning method for learning representations that employs artificial neural networks. There are three sorts of machine learning techniques: Supervised, semi-supervised, and unsupervised. Using DL, a computer model learns to do classification tasks directly from images, textual, or numeric data. Deep feature extraction with pre-trained networks such as AlexNet, VGG16, VGG19, GoogleNet, ResNet18, ResNet-50, ResNet-101, InceptionV3, InceptionResNet-V2, DenseNet-201, XceptionNet, MobileNetV2, and ShuffleNet are usually employed for classification tasks [4]. In this research, ResNet-50, which is a better version of CNN, was utilized as the basic model in the architectural proposed design to classify COVID-19 and normal patients' CXR images. The model was pre-trained on the ImageNet database for object detection. ResNet uses shortcuts between layers to reduce interference, which occurs as the network size increases in depth and complexity. With SoftMax activation, the network ends with a 1000 fully connected layer. There are a total of 50 weighted layers with 23,534,592 trainable parameters [26], [27]. The ImageNet database was used to train ResNet-50, a collection of over 14 million images divided into over 20,000 categories designed for image recognition competitions [8].

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

The critical objective of the proposed framework is to classify CXR images into normal or COVID-19. In this section, ResNet-50 was trained on a dataset containing 7232 images as a benchmark and applied to each subset, namely, CXR images in the NS Domain, by randomly dividing the database into an 80% training set and a 20% testing set. The proposed method was implemented for COVID-19 diagnosis using the MATLAB R2020a programming language on a Windows 10 computer with an Intel Core i7 processor and 16 GB of RAM. The Adam optimizer was used for weight updates, a  $1e-4$  learning rate, and five epochs; each stage uses the same MiniBatchSize. This method converts images to NS domains with different epochs used for each domain. As Figs. 4-6 depicted the accuracy and loss curves for the three domains.

In addition, experimentations were executed comprehensively to evaluate the performance of the proposed framework in terms of confusion matrix measurements, in particular, the accuracy, sensitivity, specificity, precision, F-score, and MCC rates. A confusion matrix is a table showing how an algorithm classifies data. The structure of the confusion matrix is divided into four parts, Positive True, Positive False, Negative True, and Negative False as shown in Fig. 7. As a

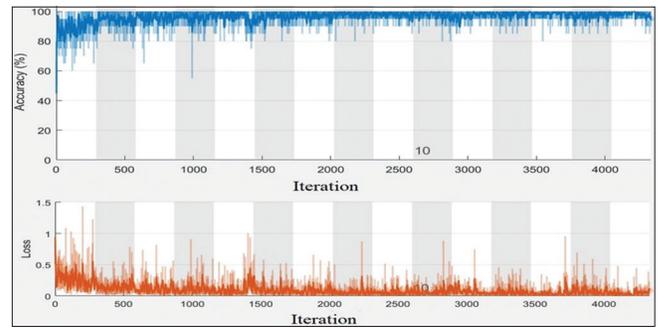


Fig. 4. The accuracy and loss curves of the suggested model that resulted from the T-Domain.

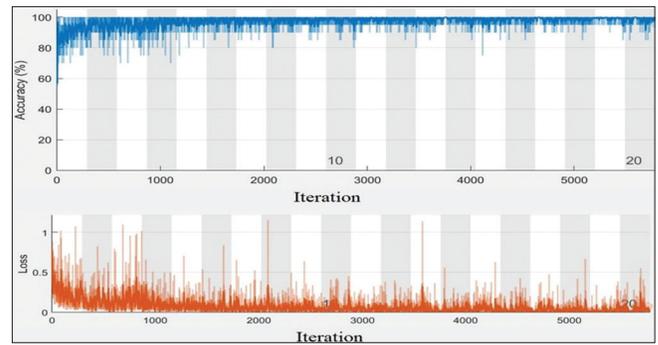


Fig. 5. The accuracy and loss curves of the suggested model resulted from the F-Domain.

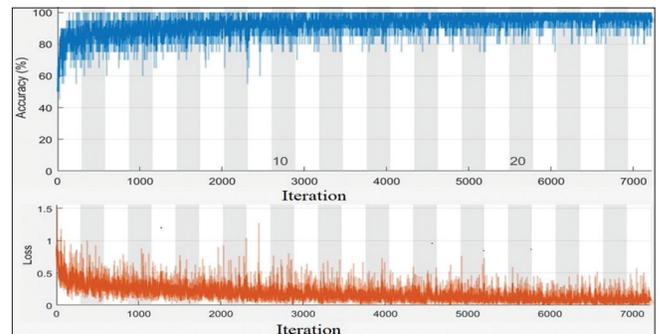


Fig. 6. The accuracy and loss curves of the suggested model that resulted from the I-Domain.

result, the images of the database were evaluated in the NS domain with different confidence values for selected models, ResNet-50 model, which was trained with five epochs, Epoch 5, Epoch 10, Epoch 15, Epoch 20, and Epoch 25. Finally, we calculate the average of each domain and compared with the average of other domains.

The model achieved an overall accuracy of about 98.05% in the F-domain on the testing set, as shown in Table 1. Furthermore, the highest sensitivity rate acquired in the T-domain had a value of 98.01%, as illustrated in Table 2.

The tables illustrated the model performance evaluation based on specificity, precision, F-score, and MCC, as shown in Tables 3-6. First, the specificity scale of the model yields

the best result in the F-domain by scoring 98.54% and ultimately outperforming other parts (Table 3). It was found that F-domain improved the highest average prediction specificity and precision to reach 98.54%, whereas the average specificity and precision of the F-domain was the lowest, scoring of 92.15% and 92.42%, respectively (Tables 3 and 4). Furthermore, the same fact has been determined to classify COVID-19 and regular patients CXR images by examining other performance measures (F1-score and MCC) to assess the proposed framework. The outcomes presented that the F-domain reached the maximum F1-score and MCC rates of 98.06% and 96.12% performing ResNet-50, respectively (Tables 5 and 6). From the above experimental results, it is clearly evident that the domain of F has better results in all measures except sensitivity, which effectively discriminates COVID-19 cases from regular patients CXR images more precisely, which may help doctors make a precise diagnosis depending on their clinical specialists as well as the recommended platform as a proper diagnosis tool.

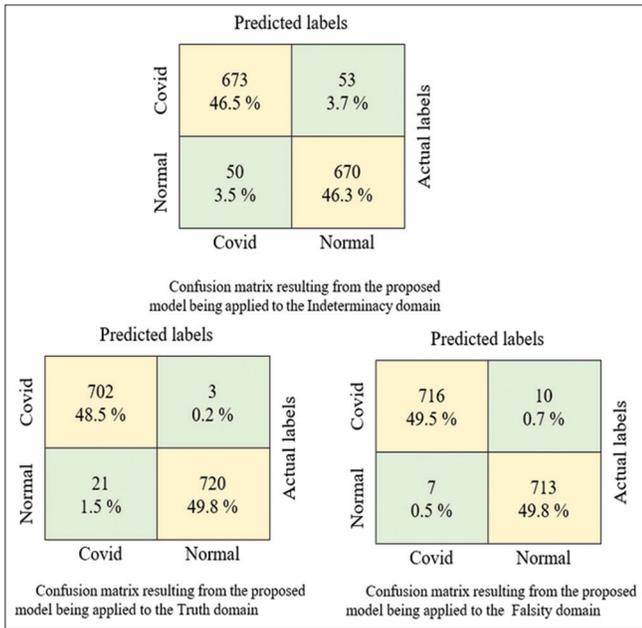


Fig. 7. Confusion matrix of the proposed model.

Using the same database and computational environment, the performance of the recommended scenarios was also tested using the misclassification error rate metric. As confirmed in Fig. 8, the misclassification error rates for the recommended scenarios were calculated. The consequences verified that the ResNet-50 Falsity domain results in a minor misclassification error of 1.95% rate, which approved that the proposed scenario outperforms all other scenarios by a significant margin. Therefore, this scenario was considered as a potential classification method for COVID-19 CXR images.

Finally, the proposed system's performance was compared to some state-of-the-art techniques, as shown in Table 7.

TABLE 1: Evaluation accuracy of overall epochs

NS Domain	Number of Epoch					Average (%)
	EP5	EP10	EP15	EP20	EP25	
I	87.07	89.21	90.49	89.83	92.32	89.78
T	97.68	97.44	98.34	97.68	97.96	97.82
F	97.51	97.99	98.31	98.55	97.89	<b>98.05</b>

EP5: Epoch 5, EP10: Epoch 10, EP15: Epoch 15, EP20: Epoch 20, EP25: Epoch 25, The best result per row is highlighted in bold

TABLE 2: Evaluation sensitivity of overall epochs

NS Domain	Number of Epoch					Average (%)
	EP5	EP10	EP15	EP20	EP25	
I	83.61	88.76	88.81	87.70	91.22	88.02
T	96.83	97.06	99.57	98.05	98.54	<b>98.01</b>
F	97.23	96.96	99.23	98.15	96.46	97.61

EP5: Epoch 5, EP10: Epoch 10, EP15: Epoch 15, EP20: Epoch 20, EP25: Epoch 25, The best result per row is highlighted in bold

TABLE 3: Evaluation specificity over all epochs

NS Domain	Number of Epoch					Average (%)
	EP5	EP10	EP15	EP20	EP25	
I	92.71	89.84	92.41	92.23	93.54	92.15
T	98.60	97.84	97.17	97.33	97.43	97.67
F	97.82	99.08	97.42	98.95	99.43	<b>98.54</b>

EP5: Epoch 5, EP10: Epoch 10, EP15: Epoch 15, EP20: Epoch 20, EP25: Epoch 25, The best result per row is highlighted in bold

TABLE 4: Evaluation precision of overall epochs

NS Domain	Number of Epoch					Average (%)
	EP5	EP10	EP15	EP20	EP25	
I	93.08	89.90	92.74	92.67	93.71	92.42
T	98.62	97.86	97.10	97.30	97.37	97.65
F	97.82	99.10	97.37	98.96	99.45	<b>98.54</b>

EP5: Epoch 5, EP10: Epoch 10, EP15: Epoch 15, EP20: Epoch 20, EP25: Epoch 25, The best result per row is highlighted in bold

TABLE 5: Evaluation of F-score over all epochs

NS Domain	Number of Epoch					Average (%)
	EP5	EP10	EP15	EP20	EP25	
I	87.84	89.28	90.71	90.11	92.43	90.07
T	97.71	97.45	98.32	97.67	97.94	97.82
F	97.52	98.02	98.29	98.55	97.93	<b>98.06</b>

EP5: Epoch 5, EP10: Epoch 10, EP15: Epoch 15, EP20: Epoch 20, EP25: Epoch 25, The best result per row is highlighted in bold

**TABLE 6: Evaluation of MCC over all epochs**

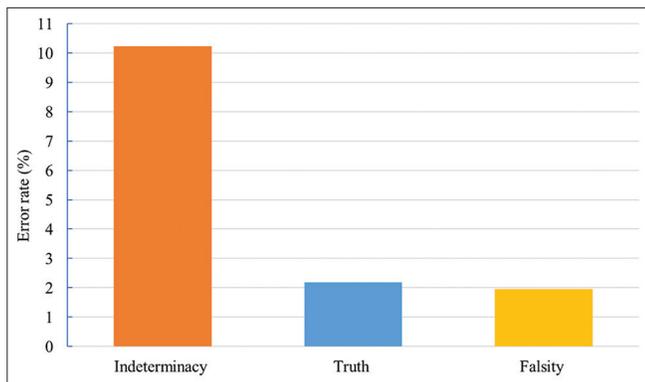
NS Domain	Number of Epoch					
	EP5	EP10	EP15	EP20	EP25	Average (%)
I	75.21	78.51	81.10	79.80	84.70	79.86
T	95.40	94.89	96.71	95.37	95.94	95.66
F	95.03	96.01	96.63	97.10	95.84	<b>96.12</b>

EP5: Epoch 5, EP10: Epoch 10, EP15: Epoch 15, EP20: Epoch 20, EP25: Epoch 25, The best result per row is highlighted in bold

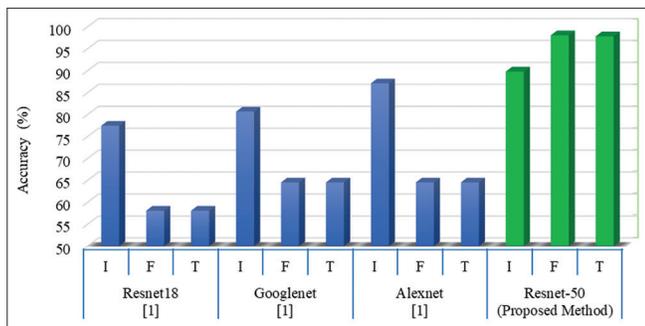
**TABLE 7: Comparison with the current state-of-art/relevant studies**

Articles	Techniques	Database	Accuracy %
Affi <i>et al.</i> [28]	CNN-DenseNet161	11,197 CXR images	91.20
Abd Elaziz <i>et al.</i> [29]	MobileNetV3+Aqu	21165 CXR images	92.40
Ahmad and Wady [30]	CT, GWT, and LGIP	7232 CXR images	96.18
Walvekar and Shinde [31]	ResNet-50	359 CXR images	96.23
Apostolopoulos and Mpesiana [32]	MobileNetv2	1427 CXR images	96.78
Proposed	ResNet-50+NS	7232 CXR images	<b>98.05</b>

The best result per row is highlighted in bold



**Fig. 8.** Misclassification error in the NS Domain.



**Fig. 9.** Comparison of system performance for a different scenario.

Compared to other methods, the proposed system produced excellent outcomes, particularly in average classification accuracy. As a final tool for proposed framework performance evaluation, a comparison has been made with the results obtained from the proposed framework and the results of paper [1] as shown in Fig. 9. The experimentations from Fig. 9 besides obviously confirmed that the proposed system

attained the highest result utilizing ResNet-50. This is due to the combined ResNet-50, and NS Domain approaches that helped the model show higher accuracy. Furthermore, the best result was obtained with an overall accuracy of 98.05% compared to the previous studies.

## 5. CONCLUSION

COVID-19 is the virus that has demolished the world’s states and placed everyone under massive quarantine. The virus attacked the world’s stability and ushered the world into a new area of instability and chaos. Using technology to control the spread of the virus through the detection of infected patients still requires more work. The work undertaken in this paper aims to serve the people and help the COVID specialist identify the patients more accurately. The study applied the fundamental principles of the NS set. The regulations include True (T) images, Indeterminacy (I) images, and Falsity (F) images on the CXR images database that belonged to both COVID-19 and regular people. Unlike the previous studies, the collected images were transformed into a NS domain trained on the DL technique, and ResNet-50 was used as a transfer learning method to train it on the database. As a result, the model scored 98.05% average accuracy, outperforming other accuracy achieved by the previous studies on a similar database.

## REFERENCES

- [1] N. E. M. Khalifa, F. Smarandache, G. Manogaran and M. Loey. “A study of the neutrosophic set significance on deep transfer learning models: An experimental case on a limited COVID-19 chest X-ray

- dataset". *Cognitive Computation*, vol. 2021, p. 0123456789, 2021.
- [2] S. Saadat, D. Rawtani and C. M. Hussain. "Environmental perspective of COVID-19". *Science Total Environment*, vol. 728, p. 138870, 2020.
  - [3] S. P. Kaur and V. Gupta. "COVID-19 Vaccine: A comprehensive status report". *Virus Research*, vol. 288, p. 198114, 2020.
  - [4] P. K. Sethy, S. K. Behera, P. K. Ratha and P. Biswas. "Detection of coronavirus disease (COVID-19) based on deep features and support vector machine". *International Journal of Mathematical Engineering and Science*, vol. 5, no. 4, pp. 643-651, 2020.
  - [5] N. Sharma, V. Jain and A. Mishra. "An analysis of convolutional neural networks for image classification". *Procedia Computer Science*, vol. 132, no. lccids, pp. 377-384, 2018.
  - [6] S. F. Ali, H. El Ghawalby and S. A.A. "From Image to Neutrosophic Image". In: *Neutrosophic Sets and System*. Port Fuad, Egypt: Port Said University, Faculty of Science, Department of Mathematics and Computer Science Apr. 2015, pp. 1-13.
  - [7] S. Lawton. "Detection of COVID-19 from CT Lung Scans Using". Paper, 2021.
  - [8] A. Narin, C. Kaya and Z. Pamuk. "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks". *Pattern Analysis Applications*, vol. 24, no. 3, pp. 1207-1220, 2021.
  - [9] T. Ilyas, D. Mahmood, G. Ahmed and A. Akhunzada. "Symptom analysis using fuzzy logic for detection and monitoring of covid-19 patients". *Energies*, vol. 14, no. 21, p. 7023, 2021.
  - [10] V. J. Sharmila and J. Florinabel. "Deep learning algorithm for COVID-19 classification using chest X-ray images". *Computational and Mathematical Methods in Medicine*, vol. 2021, p. 9269173, 2021.
  - [11] S. Hira, A. Bai and S. Hira. "An automatic approach based on CNN architecture to detect Covid-19 disease from chest X-ray images". *Applied Intelligence*, vol. 51, no. 5, pp. 2864-2889, 2021.
  - [12] F. Saiz and I. Barandiaran. "COVID-19 detection in chest X-ray images using a deep learning approach". *International Journal of Interactive Multimedia And Artificial Intelligence*, vol. 6, no. 2, p. 4, 2020.
  - [13] A. Singh, A. Kumar, M. Mahmud, M. S. Kaiser and A. Kishore. "COVID-19 infection detection from chest X-ray images using hybrid social group optimization and support vector classifier". *Cognitive Computation*, vol. 2021, p. 0123456789.
  - [14] A. Helwan, M. K. S. Ma'Aitah, H. Hamdan, D. U. Ozsahin, and O. Tuncyurek. "Radiologists versus deep convolutional neural networks: A comparative study for diagnosing COVID-19". *Computational and Mathematical Methods in Medicine*, vol. 2021, pp. 5527271, 2021.
  - [15] M. Alruwaili, A. Shehab and S. Abd El-Ghany. "COVID-19 Diagnosis using an enhanced inception-resnetV2 deep learning model in CXR images". *Journal of Healthcare Engineering*, vol. 2021, no. 4, pp. 1-16, 2021.
  - [16] V. N. M. Aradhya, M. Mahmud, D. S. Guru, B. Agarwal and M. S. Kaiser. "One-shot cluster-based approach for the detection of COVID-19 from chest X-ray images". *Cognitive Computation*, vol. 13, no. 4, pp. 873-881, 2021.
  - [17] D. Ji, Z. Zhang, Y. Zhao and Q. Zhao. "Research on classification of COVID-19 chest X-ray image modal feature fusion based on deep learning". *Journal of Healthcare Engineering*, vol. 2021, pp. 6799202, 2021.
  - [18] P. Gaur, V. Malaviya, A. Gupta, G. Bhatia, R. B. Pachori and D. Sharma. "COVID-19 disease identification from chest CT images using empirical wavelet transformation and transfer learning". *Biomedical Signal Processing and Control*, vol. 71, p. 103076, 2021.
  - [19] T. S. Qaid, H. Mazaar, M. Y. H. Al-shamri, M. S. Alqahtani, A. A. Raweh and W. Alakwaa. "Hybrid deep-learning and machine-learning models for predicting COVID-19". *Computational Intelligence and Neuroscience*, vol. 2021, p. 9996737, 2021.
  - [20] M. Turkoglu. "COVIDetectioNet: COVID-19 diagnosis system based on X-ray images using features selected from pre-learned deep features ensemble". *Applied Intelligence*, vol. 51, no. 3, pp. 1213-1226, 2021.
  - [21] M. S. Al-Ani and D. M. Al-Ani. "Review study on sciencedirect library based on coronavirus Covid-19". *UHD Journal of Science and Technology*, vol. 4, no. 2, pp. 46-55, 2020.
  - [22] V. Bahel, S. Pillai. "Detection of COVID-19 Using chest radiographs with intelligent deployment architecture". In: A. E. Hassanien, N. Dey, S. Elghamrawy, editors. *Big Data Analytics and Artificial Intelligence against COVID-19: Innovation Vision and Approach*. Vol. 78. Studies in Big Data, Springer, Cham, 2020.
  - [23] S. H. Wady, R. Z. Yousif and H. R. Hasan. "A novel intelligent system for brain tumor diagnosis based on a composite neutrosophic-slantlet transform domain for statistical texture feature extraction". *Biomed Research International*, vol. 2020, p. 8125392, 2020.
  - [24] O. G. El Barbary, R. A. Gdairi. "Neutrosophic logic-based document summarization". *Journal of Mathematics*, vol. 2021, pp. 9938693, 2021.
  - [25] A. Rashno and S. Sadri. "Content-based Image Retrieval with Color and Texture Features in Neutrosophic Domain". In: *3<sup>rd</sup> International Conference on Pattern Image Analysis IPRIA*, pp. 50-55, 2017.
  - [26] E. Rezende, G. Ruppert, T. Carvalho, F. Ramos and P. De Geus. "Malicious Software Classification Using Transfer Learning of ResNet-50 Deep Neural Network". In: *Proceeding 16<sup>th</sup> IEEE International Conference Machine Learning Application*, pp. 1011-1014, 2017.
  - [27] K. He, X. Zhang, S. Ren and J. Sun. "Deep residual learning for image recognition". *2016 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770-778, 2016.
  - [28] A. Affi, N. E. Hafsa, M. A. S. Ali, A. Alhumam and S. Als Salman. "An ensemble of global and local-attention based convolutional neural networks for COVID-19 diagnosis on chest X-ray images". *Symmetry*, vol. 13, no. 1, pp. 1-25, 2021.
  - [29] M. Abd Elaziz, A. Dahou, N. A. Alsaleh, A. H. Els Sheikh, A. I. Saba and M. Ahmadein. "Boosting covid-19 image classification using mobilenetv3 and aquila optimizer algorithm". *Entropy*, vol. 23, no. 11, pp. 1-17, 2021.
  - [30] F. H. Ahmad and S. H. Wady. "COVID19 infection detection from chest Xray images using feature fusion and machine learning". *The Scientific Journal of Cihan University Sulaimaniya*, vol. 5, no. 2, pp. 10-30, 2021.
  - [31] S. Walvekar and S. Shinde. "Detection of COVID-19 from CT Images Using resnet50". In: *2<sup>nd</sup> International Conference on Communication and Information Processing*, 2020. Available from: <https://www.ssrn.com/abstract=3648863> [Last accessed on 2022 Aug 12].
  - [32] I. D. Apostolopoulos and T. A. Mpesiana. "Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks." *Physical and Engineering Sciences in Medicine*, vol. 43, no. 2, pp. 635-640, 2020.