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Novel Architecture for Image Classification Based on Rough Set

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ABSTRACT

The Computed Tomography (CT) scan images classification problem is one of the most challenging problems in recent years. Different medical treatments have been developed based on the correctness of CT scan images classification. In this work, a novel deep learning architecture is proposed to correctly diagnose COVID-19 patients using CT scan images. In fact, a new classifier based on rough set theory is suggested. Extensive experiments showed that the novel deep learning architecture provides a significant improvement over well-known classifier. The new classifier produces 95% efficiency and a very low error rate on different metrics. The suggested deep learning architecture coupled with novel tolerance outperforms the other standard classification approaches for the detection of COVID-19 using CT-Scan images.

KEYWORDS

CT-Scan, Novel Tolerance Rough Set Classification, Deep Neural Network, Deep Tolerance Rough Set Architecture

1. INTRODUCTION

Many pandemic viruses, such as smallpox (Henderson, 2009) and Spanish influenza (Spreeuwenberg et al., 2018) have killed millions of people in recent years. In the years 2003, 2009, and 2012, various pandemics were observed, including H1N1 influenza (Pandemic H1N1 2009), Severe Acute Respiratory Syndrome Corona Virus (SARS-CoV) (Pandemic SARS., 2003), and the Middle East Respiratory Syndrome Corona Virus (MERS-CoV) (Pandemic MER's-cov., 2012). SARS and MERS have alike symptoms, but SARS is more virulent, and MERS is more contagious. The disease was initially unknown, but experts identified its signs as being similar to influenza and coronavirus diseases (Chen et al., 2020; Huang et al., 2020 ; Lima, 2020; Struyf et al., 2020). As of November 2021, there were more than 253,684,701 confirmed cases of the disease, 5,110,870 are death cases, and 229,391,450 recovered cases are addressed all around the world. First, the people are infected with the virus and act as carriers, but they may not show any symptoms. These people are more likely to spread the virus since they may be unaware of its presence.

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Individuals with a minor fever, cough, headache, or probable conjunctivitis fall into the second category. An upper respiratory tract infection is the main indicator in the second category. In the third category of people, the symptoms are similar to those in the second group, but they are more severe and may necessitate hospitalization. Treatment as soon as possible can help reduce symptoms and prevent death. Acute cases of COVID 19 might reason Acute Respiratory Distress Syndrome (ARDS) and Pneumonia in the fourth category. It is deadly at this stage. This contamination is highly infectious and spreads even more rapidly through respiratory droplet infection compared to other kinds of flu. Though patches with COVID-19 pneumonia with a specific pattern may be seen on CT scans by naked human eyes, it is simple to overlook those minor and minimally diseased areas, especially in the initial stages. Because of this, radiologists need to be adequately trained to make an early and accurate diagnosis, which is crucial for prompt treatment as well as for population screening and response. Initial COVID-19 detection is essential for both patient care and epidemiology because it enables individuals to be isolated and the epidemic to be contained (World Health Organization, 2020; Wang et al., 2020; Azar & Hassanien, 2022). However, due to the time-consuming and difficult aspect of professional training, there is a dearth of qualified radiologists, making correct diagnoses all the more difficult given the new increase in cases. An automated and reliable approach is urgently needed to increase the consistency and ease of COVID-19 CT based diagnosis. The United States, the United Kingdom, and a number of other nations have adopted and utilized vaccines made by Pfizer (USA), AstraZeneca (UK), and Moderna (USA). Based on the findings of clinical trials, the three effective vaccinations are thought to have attained the target of 50% effectiveness and are safe to use without any noticeable adverse effects. (Ledford et al., 2020; Jafari et al., 2022). Many countries, including some Latino countries, such as Columbia, Uruguay, Chile, and Brazil along with other countries such as Laos, Turkey and Indonesia have recently approved the vaccine produced by Sinovac Life Sciences in China (Kim et al., 2021)

1.1 Background Study for COVID-19

The symptoms are identical to those of the seasonal flu; therefore, COVID-19 cannot be identified only based on the symptoms. As a result, diagnostic testing is necessary for identifying affected people. Severe Acute Respiratory Syndrome Corona Virus- 2 (SARS-CoV-2) is a Ribo Nucleic Acid (RNA) virus. Reverse Transcription Polymerase Chain Reaction (RT-PCR) is a study of chemical processes techniques that can be utilized to identify these genes. RT-PCR is dependent on obtaining enough viral RNA, which is commonly obtained from a patient's nasopharyngeal (throat) swabs. The RT-PCR test is the main standard for diagnosing COVID-19 which is minimally invasive, and duration of the time is intensive (Logunov et al., 2021). Due to the difficulty in diagnosing the disease, the amount of viral RNA used to trigger the reaction is changed, raising the chance of a failure in the test for detect the result. A false negative of SARS-CoV-2 infection is defined as a person who has a supposed infection and receives a negative result on an initial RT-PCR test but then receives a positive result on a follow-up test. False-negative cases have significant consequences for infected people's isolation and transmission risk. Hence RT-PCR test can have trouble discriminating between true positive and true negative COVID-19 infected people. The use of imaging techniques such as X-rays and Computed Tomography (CT) scans is one of the most effective ways to diagnose COVID-19 (Huang et al.,2020). since, in the second wave, the lung is quickly being damaged by the Coronavirus. The Chest X-Ray (CXR) is one of the most known non-invasive therapeutic adjuncts for identifying such visual responses associated with SARS-COV-2 infection and it is frequently utilized as the first investigation for COVID-19. The results of the CXR were related to vital signs and blood tests, such as neutrophil counts, D-dimer, and C reactive protein, all of which have been linked to a poor prognosis in COVID-19. One of the most notable limitations of chest X-ray investigations is that they are insufficiently sensitive in detecting Ground Glass Opacity (GGO), hence they cannot detect early COVID-19 stages (Zu et al., 2020). CT is a provide more sensitive imaging technique for the chest, with larger reliability and accuracy than chest X-rays. CT scanning may be a practical tool for screening and diagnosing. CT scan images of the chest are essential for monitoring and evaluating

COVID-19 patients with severe respiratory symptoms. CT image allows doctors to see the shape, size, density, and texture of interior structures. CT scans create a series of slices of a specific body region that do not overlap with the various body structures. In endemic areas, a CT scan of the chest is considered a significant tool for COVID-19 detection. The predominant symptom of COVID-19 is patchy Ground-Glass Opacities, which are hazy white patches in the lungs, as shown on CT scans. CT images can detect apparent changes and a variety of anomalies in COVID-19-affected lungs. Furthermore, both doctors and research scientists face a significant challenge in combating COVID-19.

1.2 Research Motivation

Rough image processing encompasses all methods and strategies for comprehending, representing, and processing images, segments, and features as rough sets. Because of greyness and/or spatial uncertainties, boundaries between object regions in greyscale images are frequently badly defined Pal et al., 2001; Pal, 2005). The distinct items can be described as rough sets with outer and inner estimations to address the uncertainty. The equivalence relation is partitioned as pixels lying within each uncorrelated frame over the image. The equivalence relation distinguishes Pawlak's rough set-based classification algorithms, which are only appropriate for non-continuous datasets. When dealing with continuous data and the Pawlak model, the cost of computation escalates. As a result, to solve this issue, various modifications of the rough set theory were familiarized. In this study, a Novel Tolerance Rough Set (NTRSC) based similarity is used for classification, which increases classification performance. A tolerance rough set can address the actual-valued data while also maintaining data semantics, making it appropriate for classification. In this way, any data misfortune can be minimized by using a tolerance rough set model that can perform well on actual esteemed (and sharp) data. Deep Learning (DL) approach plays an important role and is a simple method and is composed of several non-linear variations. DL techniques became more competent and used for better efficiency, lack of human contribution in feature extraction, and detection. The application of Deep Learning (DL) to reliably diagnose illnesses and analyze imagery data has the ability to change the medical industry. Deep Learning algorithms have made it possible to build an end-to-end model that can generate final classification labels from raw medical image pixels. With an aim to new architecture approach set using rough sets and deep learning architecture for many actual practical applications, this study will make use of deep learning and soft computing.

Rough sets have characteristics like dimensionality reduction, and uncertainty analysis, to discover structural relationships within imprecise and noisy data, identify partial dependencies in data, and gain in computation time. In this way, uncertainty arising from regions in data, as well as the computation time in decision-making would also get reduced if rough sets are used. Future challenges can be solved by adapting deep learning architecture. Deep learning has shown state-of-the-art performance on a variability of tasks involving classification, segmentation, and other aspects of medical imaging. Deep learning methods have had a significant impact on the automation of medical image processing tasks, displaying state-of-the-art accuracy. The majority of Deep Learning methods implementations focus on digital images from histopathology, Computer Tomography, mammography, and X-rays. To determine whether a disease is present or not in medical imaging, deep learning approaches are typically used. Numerous applications and data types can be served using the same neural network-based method. For that reason, Deep TRS architecture consists of different layers, where features and different stages are learned; thereby providing a better structural representation of the data. The size and shape of lower and upper regions that evolved in different layers would enable better structural representation of the data, and the patterns therein and hence the derivation of knowledge. These merits of the Rough Set and Deep Learning produce the best results on Novel Deep Tolerance Rough Set-based Architecture as a proposed solution for classification.

1.3 Research Objective

The main objective is to apply the image processing technique for COVID-19 diagnosis and to develop a computer-aided method for timely detection and treatment of the COVID-19 virus. The adoption of

computer-aided systems in disease detection and monitoring will speed up diagnosis and treatment. Deep Learning and Machine Learning Automatic diagnostic systems commonly use methods based on computer-based algorithms to aid clinicians in their decisions and reduce diagnosis time.

1. The novel contribution of this study is the findings of the powerful performance of other existing classification techniques and deep learning models, which can yield superior classification accuracy for the COVID-19 CT dataset.
2. This study proposes a novel Deep TRS Architecture (DTRSA) learning model proposed for the COVID-19 classification.
3. The classification algorithms are assessed using appropriate classification measures.

1.4 Research Contribution

The main contributions of this research work are as follows:

a. Novel Tolerance Rough Set Classification (NTRSC) is a machine learning technique which can handle uncertain and incomplete data, which makes it well-suited for medical image analysis.
b. Deep Neural Network (DNN) is a type of artificial neural network that can be used better for image classification tasks.
c. The proposed DTRSA architecture has hybridized NTRSC and DNN network to create a novel approach for COVID-19 CT scan image classification, achieving higher accuracy than existing methods.

The literature review of related works on COVID image analysis and Tolerance Rough Set theory is presented in Section 2 of this article. The procedures and materials used to identify COVID-19 in CT-Scan pictures are described in Section 3. The background investigation on Tolerance Rough Set is covered in Section 4. The empirical results of the study are covered in great depth in Section 5. Section 6 concludes by outlining the conclusion and the direction for future study.

2. RELATED WORK

Deep learning technology, which emerged from Artificial Neural Networks (ANN), has become a hot topic in computer science and is widely employed in sectors such as healthcare, image recognition, text analytics, cybersecurity, and many more (Dudekula et al., 2023; Fati et al., 2022; Boulmaiz et al., 2022, Zaidi et al. 2022; Ganesan et al., 2022; Abbas et al., 2022; Azar et al., 2021a,b; Ibrahim et al., 2020; Ramadan et al., 2022; Aslam et al., 2021).

Gozes et al. (2020) introduced an automated deep learning-based CT image processing tool for detecting, measuring, and trailing COVID-19. They also showed that it can distinguish between patients and healthy individuals. They established classification findings for Coronavirus versus Non-coronavirus cases per thoracic CT examinations using datasets of Chinese control affected patients. They achieved classification results of 0.996 AUC (95 percent CI: 0.989-1.00) using the deep-learning image analysis method. 98.2% sensitivity and 92.22% specificity (high sensitivity point) and 96.44% sensitivity and 98.4% specificity are two potential working points (high specificity point).

Li et al. (2020) developed and assessed a three-dimensional deep learning model to detect COVID-19. The 2D local and 3D global illustrative features can both be extracted using this approach. They demonstrated that this model successfully detected COVID-19 with high sensitivity (90 percent [95 percent Confidence Interval (CI): 83 percent, 94 percent]) and specificity (96 percent [95 percent Confidence Interval 93 percent, 98 percent]) using an independent testing data set. The COVID-19 AUC value was 0.96 and the Community-Acquired Pneumonia (CAP) AUC value was 0.95.A 3D deep learning system was proposed to detect COVID-19.

Xu et al. (2020) proposed a classification network that was created using deep learning technologies to discriminate COVID-19 from Influenza-A Viral Pneumonia (IAVP). The traditional Residual Neural Network (ResNet) was employed for feature extraction in terms of the design of the network. Evaluating models with and without a location-attention mechanism. The research indicates that the proposed approach may more effectively separate COVID-19 cases from other cases. The experimental results produce an accuracy of 86.7%, precision of 81.3%, and F1-Score of 83.9% for COVID-19 classification.

Wang et al. (2021) proposed that before the pathogenic test, artificial intelligence approaches might be able to extract specific graphical components from COVID-19 and provide a clinical diagnosis. Framework for Deep Learning (DL) algorithms for Region Of Interest (ROI) image extraction. Classification and prediction are then carried out via the full connection layer. The specificity and sensitivity of the internal validation were 0.88 and 0.87, respectively, yielding a total accuracy of 89.5 percent. With a specificity of 0.83 and sensitivity of 0.67, the external testing dataset displayed overall accuracy of 79.3%.

Rahimzadeh et al. (2021) presented an entirely automatic technique for detecting COVID-19 from lung High-Resolution CT (HRCT) data. Three distinct deep convolution networks were trained to categorize CT scan images as COVID-19 or normal images. Their model, which utilizes ResNet50V2, a modified feature pyramid network, and the suggested architecture, produced the best results. Researchers performed method to the test on more than 7796 images, nearly 245 individuals and 41,892 photos of various opacity. The model indicated an overall accuracy for single image classification of 98.49 percent.

Wang et al. (2021) designed a system that consists of classification and segmentation, that will improve COVID-19 detection performance and save doctors between 30 and 40 percent of their detection time. For the classification tasks, researchers tested a number of state art classification models, including ResNet-50, Inception networks, DPN-92, and Attention ResNet50. Using 723 positives for COVID-19 from five hospitals, they are able to identify a range of pulmonary illnesses on the test dataset with a sensitivity of 0.974 and specificity of 0.922.

A quick and accurate method for diagnosing COVID-19 using artificial intelligence is suggested by (Ardakani et al., 2020). Using ten well-known convolutional neural networks, COVID-19 infection and NON-COVID-19 groups were separated. The two networks with the best performance were ResNet-101 and Xception. ResNet-101 was able to distinguish COVID-19 patients from cases without COVID-19 with an Area Under the ROC Curve (AUC) of 0.994. The Xception AUC was 0.994. A high-sensitivity model called ResNet-101 can be used to describe and locate COVID-19 infections.

Song et al. (2021) proposed an accurate computer-aided approach to help doctors recognize COVID-19-infected individuals from CT images is essential. For comparison and modeling, they gathered chest CT images from 86 healthy persons, 100 patients with bacterial infections, and 88 COVID-19 affected people from hospitals in two Chinese provinces. Using this data, a deep learning-based CT diagnosis method was developed to find COVID-19 patients. The fact findings demonstrated that, with an AUC of 0.95, recall, and precision of 0.79, the model could successfully distinguish between COVID-19 patients and patients with bacterial infections which is called bacterial pneumonia.

In Skowron & Stepaniuk (1996), the attribute reduction process is discussed, and the Tolerance relation identified by the so-called ambiguity function, or the optimistic area of a given certain of instances was identified as invariants. A tolerance information system determines the tolerance approximation spaces, which are used to define the lower and upper set approximations. The solutions for feature selection are represented by tolerance reductions and relative tolerance reducts.

In Lavanya & Inbarani (2017), a combination method is proposed based on Principal Component Analysis (PCA) and Tolerance Rough Similarity (TRS) for face identification. The hybrid strategy produces a greater detection rate as compared to other widely used methods like Euclidean distance and cosine similarity. The PCA-TRS has provided a 97% accuracy rate and a 1.54% error rate. Table 1 depicts the summary of the related work.

3. GLCM FEATURE EXTRACTION

The COVID-CT collection includes 360 affirmative COVID19 occurrences, 397 NON-COVID CT scans, and 349 COVID CT illustrations. These CT scans have varied the highest and lowest values for their height and width (maximum 1853, average 491 and minimum 153), respectively. To maintain homogenous quality in the final dataset for research, all images were transformed to Portable Network Graphics (PNG) format. All images were converted to Portable Network Graphics(.png) format in order to keep homogeneous qualities in our final dataset for research. Additionally, images were downsized to 256*256 for both COVID and NON-COVID.

Medical image analysis necessitates preprocessing, by applying gaussian noise to the image. Various Filtering techniques are applied to the images. In comparison to other filtering methods, the median filter produces the most effective results. The median filter algorithm swaps out the individual value in the image for the average values. In order to calculate the average element, first arrange each of the gray levels in increasing order. Then, replace the calculated pixel number with the median pixel valuation. For a variety of interferences, the median filter can offer effective noise suppression with reduced distortion. Then, the image was segmented using Otsu's thresholding technique as well as appropriate erosion morphological operations to filter out the unwanted pixels. To highlight the area of interest and generate the mask, operations are performed on an image. Finally, the Gray-Level Co-occurrence Matrix (GLCM) is a numerical technique for evaluating textures that determines the mapping association between pixels. For different offsets, several GLCMs can be measured. The offsets explain spatial associations that vary in depth and orientation. With a distance D of any given integer between 1 and the imaging dimension, the angles are 0°, 45°, 90°, and 135°.

In this research, GLCM texture features are taken which are Homogeneity, Contrast, ASM, Correlation, Dissimilarity, and Energy. Figure 1 (A) and 2 (A) represents the original COVID and NON-COVID images. Figure 1 (B) and 2 (B) depicts the median filter on the images. Figure 1 (C) and 2 (C) describes Otsu's Segmentation and Figure 1 (D) and 2 (D) reveals the morphological operations applied to both types of images.

4. SIMULATION RESULTS AND DISCUSSION

In 1980, Pawlak invented Rough Set, a computational technique for addressing vulnerability. The Rough Set (RS) theory can be used as a technique to cope with ambiguity and uncertainty in datasets. The majority of applications for rough sets are centered on classification issues (Inbarani et al., 2022, 2020, 2018, 2015a,b, 2014a,b,c; Jothi et al., 2022, 2020, 2019a,b, 2017, 2016, 2013). Data dependencies are the backbone of attribute reduction. In order to approximate ambiguous and hazy notions, the RS concept separates a data into a variety of related (indiscernible) groups. The rough set technique generates a set of decision rules based on a fewer number among the most important factor. A pair of crisp sets represents the lower and upper approximations set, which represent a rough

Figure 1. (A) CT-COVID Image (B) CT-COVID Image after applying Median Filter (C) Otsu Thresholding for Covid Image (D) After Morphological Operation – Erosion for COVID CT-Image

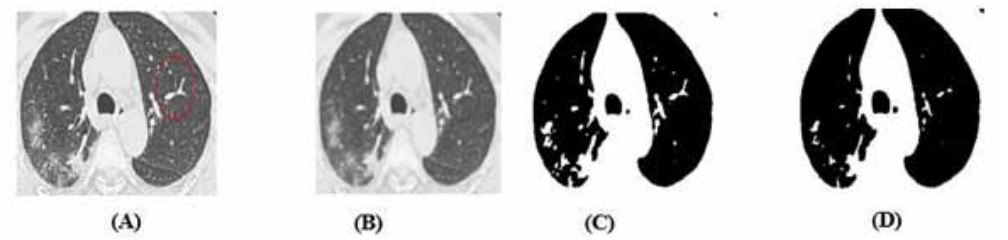


Figure 2. (A) Input NON-COVID CT Image (B) CT NON-COVID Image after applying Median_ Filter (C) After Otsu Thresholding for NON-COVID Image (D) After Morphological Operation – Erosion

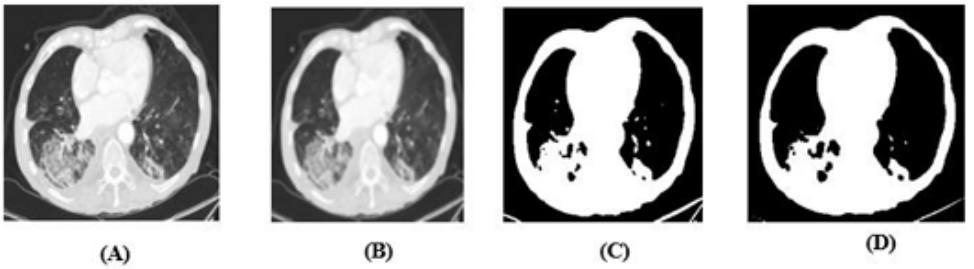


Table 1. Overview of the literature survey

AUTHOR	USED METHODS	IMAGING MODALITY	TASK	OBJECTIVE	DATASET	PERFORMANCE METRICS AND ACCURACY
Gozes et al.,2020	U-NET, RESNET50	CT	Segmentation Classification	To develop tools for coronavirus diagnosis, quantification, and tracking that are AI-based automatic CT image analysis.	Lung CT images of 6,150 50 patients had abnormal chest CT scans and had COVID-19 suspicions based on radiologist diagnoses. Cases were categorized as regular (n = 1036) or aberrant (n = 829) for each image.	Sensitivity = 98.2%, Specificity = 92.2%, and AUC = 0.996
Li et al.,2020	COVID-19 detection Neural Network (COVNet)	CT	Segmentation Classification	To provide and assess a completely computerized system for COVID-19 chest CT detection.	3,322 patients provided 4352 3D chest CT images, of which 1,292 were of COVID-19, 1,735 were of Community-Acquired Pneumonia, and 1,325 Non-Pneumonia	Sensitivity-=90 percent, Specificity = 96 percent, and AUC = 0.96
Xu et al., 2020	RESNET	CT	Classification	To design an early screening model based on deep learning to distinguish COVID-19 from Influenza-A Viral Pneumonia (IAVP) and hale patients from lung CT scans.	219 COVID, 224 Influenza-A viral pneumonia, and 175 healthy cases were depicted in 618 CT images.	Accuracy = 86.7%, Precision = 81.3%, F1-Score=83.9%
Wang et al.,2021	Modified the inception transfer-learning model	CT	Classification	To propose a methodology for DL algorithms for ROI image extraction techniques. Classification and prediction are then carried out via the full connection layer.	1,065 CT scans of COVID-19 patients, 325 images of the pathogen, and patients who had earlier been described with typical viral pneumonia 740 images	Internal validation: Accuracy = 89.5%, Specificity=0.88%, Sensitivity=0.87% External testing Accuracy =79.3%, Specificity = 0.83%, Sensitivity = 0.67%
Rahimzadeh et al.,2021	ResNet50V2, a modified feature pyramid network	CT	Classification	A fully automated system that responds quickly and accurately to find COVID-19 situations.	The dataset includes 48,260 images from 282 people who had normal CT scans and 15,589 images from 95 cases with COVID-19 infections.	Accuracy = 98.49%.

continued on following page

Table 1. Continued

AUTHOR	USED METHODS	IMAGING MODALITY	TASK	OBJECTIVE	DATASET	PERFORMANCE METRICS AND ACCURACY
Wang et al.,2021	Dual-Path Network (DPN-92), the Inception-v3, the RESidual NETwork (ResNet-50), and the Attention ResNet-50 .	CT	Segmentation Classification	To construct and implement an Artificial Intelligence technique that analyses CT images automatically and provides the possibility of infection to enable fast COVID-19 pneumonia detection.	Hospitals in Wuhan contributed the majority of the 877 confirmed patient, whereas hospice in Beijing contributed 50% of the 541 negative cases.	Sensitivity=0.974% and Specificity=0.922%
Ardakani et al., 2020	Ten well-known Convolutional Neural Networks	CT	Classification	A COVID-19 diagnosis approach utilizing artificial intelligence that is rapid and precise.	1020 CT segments from 108 individuals with COVID-19 that had been lab-verified and 86 persons with the other unusual and viral pneumonia diseases were included in the COVID-19 group.	AUC = 0.873, Sensitivity= 89.21% Specificity= 83.33%Accuracy= 86.27%.
Song et al., 2021	Details Relation Extraction Neural Network (DRENet)	CT	Classification	To produce a reliable computer-aided technique that can help clinicians recognize COVID-19-diseased individuals from CT metaphors.	Chest CT scans of 86 healthy individuals, 100 patients with bacterial pneumonia, and 88 individuals with COVID-19 from hospitals in two provinces of China for modeling and comparison.	AUC = 0.95, recall (sensitivity) of 0.96, and precision of 0.79 in patients with bacterial pneumonia For CT images, the model distinguished COVID-19 patients with a recall of 0.93 and a precision of 0.86.

set. The lower approximation collection contains the system's objects that are based on the available data. Reductions do not provide any extra details while maintaining the same level of characterization accuracy as the original data structure. Figure 3 depicts the block diagram for Deep TRS Architecture.

Rough Set Theory's primary flaw is that it is incapable of handling real and accurate data. According to RST, techniques for discretizing the information are used to address these issues. Several RST extensions that have been developed for in real values. The tolerance rough set model may reduce any data defeat and work effectively with real-valued (and crisp) information (Parthaláin & Shen, 2009) . This approach involves an assessment of accent value equivalence and describes the lower and upper approximations using these similitude metrics Tolerance rough sets have specific lower and upper estimates. (Gozes et al., 2020).

4.1 Definition 1: Tolerance Similarity Measure

Consider COVID and NON-COVID feature attribute vectors. Using the similarity metrics and compute the similarity of each COVID and NON-COVID feature vector. A similarity measure between two images denoted by the letters A and B is defined as:

$$\left(A,B\right)=D\left(T\left(A\right),T\left(B\right)\right) \tag{1}$$

Tolerance similarity in a rough set of tolerances is easily calculated using the distance function and highlights the close proximity of two patterns. Let (x , y) reflect how similar x and y are in terms of the tolerance threshold characteristic. In terms of attribute "a," x and y are comparable. τ

is the tolerance similarity threshold relation for attribute "a," whose value falls within the range τ_a [0,1]. Therefore, connect the simple distance a to the conventional similarity measure $SIM_a\left(x,y\right)$ with respect to τ. To measure the Tolerance similarity between pixels of the image,

$$SIM_a\left(x,y\right)=1-\frac{\left|a\left(x\right)-a\left(y\right)\right|}{a_{max}-a_{min}} \tag{2}$$

where 'a' stands for the property or feature and a_{max} and a_{min} represents the highest and lowest values for the features selected. For a subset of features P, Similarity can be attained as follows:

$$\left(x,y\right)\in SIM_{P,\tau}\ \ iff\prod_{a\epsilon P}SIM_a\left(x,y\right)\geq\tau \tag{3}$$

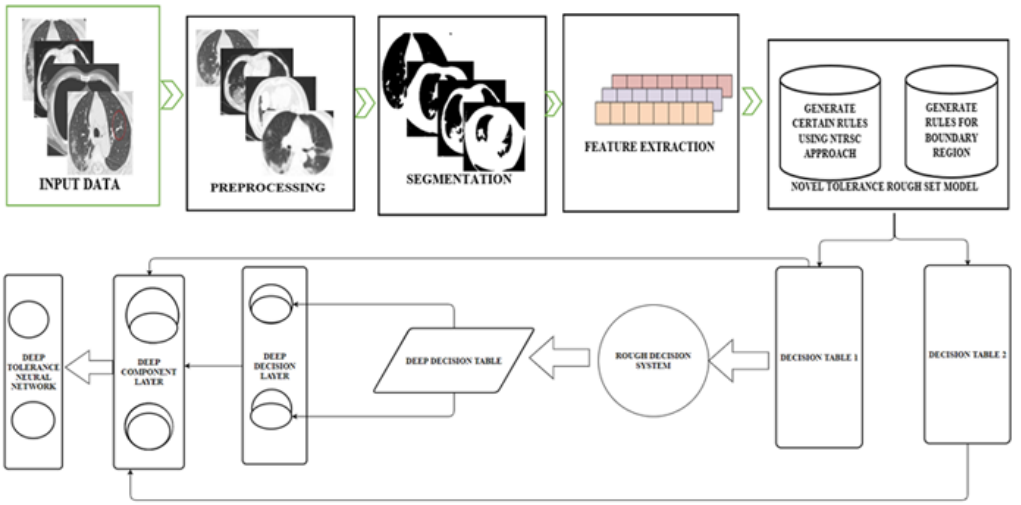
$$\left(x,y\right)\in SIM_{P,\tau}iff\ \frac{\sum_{a\epsilon P}SIM_a\left(x,y\right)}{\left|P\right|}\geq\tau \tag{4}$$

The Novel Tolerance Rough Set Classifier is shown in Algorithm 1, which also depicts the Novel Tolerance Rough Set Classifier Strategy. Steps 1 and 2 of this method consist of creating a tolerance relation for the conditional attribute and an Equivalence relation for the decision feature. In the third and fourth stages, NTRSC is used to construct inner(lower) and outer(upper) approximations of the COVID GLCM dataset constructed on Decision class D. The boundary region is calculated in the fifth step using lower and upper approximations.

The centroid for lower rules is then estimated using NTRSC lower approximations in the following phase. For each class of lower approximation rules, compute the difference between the midpoint and Boundary Rules. Finally, update the Decision value based on the closest rule.

ALGORITHM 1– NOVEL TOLERANCE ROUGH SET CLASSIFIER (NTRSC)
INPUT: The conditional attributes set (decision attribute) D = {d_1, d_2, …, d_n}.
OUTPUT: For each class, set of rules generated.

Figure 3. Block diagram for deep TRS architecture



Step 1: The conditional attributes tolerance relation as,
$\left[\ddot{A}\right]c \leftarrow C$
$\ddot{A}_C\left(x_i\right) \leftarrow \left[x\right]c$
Where $\forall\tau_C\left(x_i\right)$ referred to as, $\forall\ddot{A}_C\left(x_i\right) = \{x \mid f\left(C\left(x_i\right), B\left(x\right)\right) \leq \ddot{A}, x \in U\}$
Step 2: Develop the equivalence relation for the decision attribute using the equation $\left[x\right]_D \leftarrow D$
Step 3: Build the lower approximation space for the Tolerance rough set for each class.
$\underline{T_B X} = \{x_i \mid \ddot{A}_C\left(x_i\right) \subseteq X,\ x_i \in U\}$
Step 4: Build the upper approximation space for the Tolerance rough set for each class.
Step 5: Obtain the boundary region of the data set using the difference between the Tolerance rough set Lower and Upper approximations.
$BND_C\left(X\right) = \underline{T_B X} - \overline{T_B X}$
Step 6: Create rules using a Tolerance approximate set depending on the lower approximation for every group separately.
Step 7: Compute using Lower approximation the centroid for Lower Rules $CEN_D\left(x\right) \leftarrow T_B X$
Step 8: Compute the distance between Boundary Rules and centroid for each class.
$\forall BND_C\left(X\right)\ \forall CEN_D\left(x\right)$
$DIS_{ij} \leftarrow DIS\left(BND_C\left(D\right), CEN_D\left(X\right)\right)$
Where, $DIS_{ij} = \sum_{k=1}^{n}\sqrt{(X_{ik} - X_{jk})_2}$
Step 9: Update the minimum distance to the matching closest rule by using the equation
$TD \leftarrow MIN\left(DIS_{ij},\ CEN_D\left(X\right)\right)$
Step 10: Update the new decision Feature, $D \leftarrow TD$
Step 11: Call DTRSA (C, D)

5. DEEP TRS ARCHITECTURE (DTRSA)

Artificial Intelligence (AI) is rapidly increasing and finding new applications in a wide range of disciplines, including security, the environment, research and education, health, culture, and business (Khamis et al., 2022, 2021; Ahmed et al., 2022a,b; Hameed et al., 2022; Kazim et al., 2021; Ammar & Azar, 2020; Ali et al., 2022a,b; Soliman et al., 2020; Aziz et al., 2013a,b, 2012; Azar et al., 2023a,b, 2022, 2021c,d,e,f, 2020a,b,c,d,e,f,g,h,i,j,k,l,m,n,o, 2019a,b,c, 2018a,b, 2017, 2016a,b, 2014a,b, 2013a,b,c,d, 2012, 2007; Nasser et al., 2021; Hamida et al., 2022; Fouad et al., 2021; Azar & Serrano, 2019; Kumar et al., 2018; Khettab et al., 2018; Samanta et al., 2018, ElBedwehy et al., 2014; Mukherjee et al., 2014).

Machine Learning (ML) is a subset of artificial intelligence that creates dynamic algorithms capable of generating data-driven decisions (Hussain et al., 2023; Atteia et al., 2023; Salam et al., 2021, 2022; Mathiyazhagan et al., 2022; Ashfaq et al., 2022a,b; Fekik et al., 2021, 2018a,b; El Kafazi et al., 2021; Bouakrif et al., 2019; Sundaram et al., 2021; Hussien et al., 2020; Mjahed et al., 2020

; Sayed et al., 2019; Aboamer et al., 2019, 2014a,b; Sallam et al., 2020; Kumar et al., 2017, 2015, 2014; Banu et al., 2017, 2014; Ben Abdallah et al., 2016, 2014; Fredj et al., 2016 ; Malek and Azar, 2016a,b; Vaidyanathan & Azar, 2016; Zhu & Azar, 2015; Malek et al., 2015a,b; Ding et al., 2015; Elshazly et al., 2013a,b,c).

Machine Learning (ML) is now widely used in research and implemented in a wide range of applications, including control systems, robotics, medical diagnostics, fraud detection, autonomous driving, image and audio classification, and multimedia concept retrieval (Abed et al., 2022; Lavanya et al., 2022, 2021; Azar, & Banu, 2022; Ananth et al., 2021; Sain et al., 2022; Saidi et al., 2022; Panda & Azar, 2021; Acharyulu et al., 2021; Ajeil et al., 2020a,b; Ibraheem et al, 2020a, b; Najm et al., 2020; Liu et al., 2020, 2022; Sekhar et al., 2022; Mustafa et al., 2020; Ghoudelbourk et al., 2021; Cheema et al., 2020; Kamal et al., 2020; Humaidi et al., 2020a,b; Elfouly et al., 2021; Khan et al., 2021; Elkholy et al., 2020a; Barakat et al., 2020; Pilla et al., 2021a,b, 2020, 2019; Amara et al., 2019; Babajani et al., 2019; Habibifar et al., 2019; Gorripotu et al., 2019; Ammar et al., 2020, 2019, 2018; Pintea et al., 2018; Ben Smida et al., 2018; Ghazizadeh et al., 2018; Meghni et al., 2023, 2017a,b; Giove et al., 2013; Santoro et al., 2013; Dey et al., 2015; Elkholy et al., 2020b; Mohamed et al., 2020; Ibrahim et al., 2020; Sayed et al., 2020).

ML algorithms, once trained, discover patterns in existing data and use those patterns to produce meaningful insights from new data. Two key approaches are utilised to do this: supervised learning (with the assistance of a data analyst or domain expert) and unsupervised learning (Mohanty et al., 2021; Ahmadian et al., 2021; Abdelmalek et al., 2021, 2018; Al-Qassar et al., 2021; Humaidi et al., 2021; Kumar et al., 2019, 2015, 2014; Azar & Vaidyanathan, 2015a,b; Anter et al., 2020, 2015, 2014, 2013; Djeddi et al., 2019; Moftah et al., 2014; Hassanien et al., 2015a,b, 2014a,b; Asad et al., 2014a,b, 2013a,b; Chowdhuri et al., 2014a,b ; Emary et al., 2014a,b; Gharbia et al., 2014; Azar & Hassanien, 2015; Eid et al., 2013).

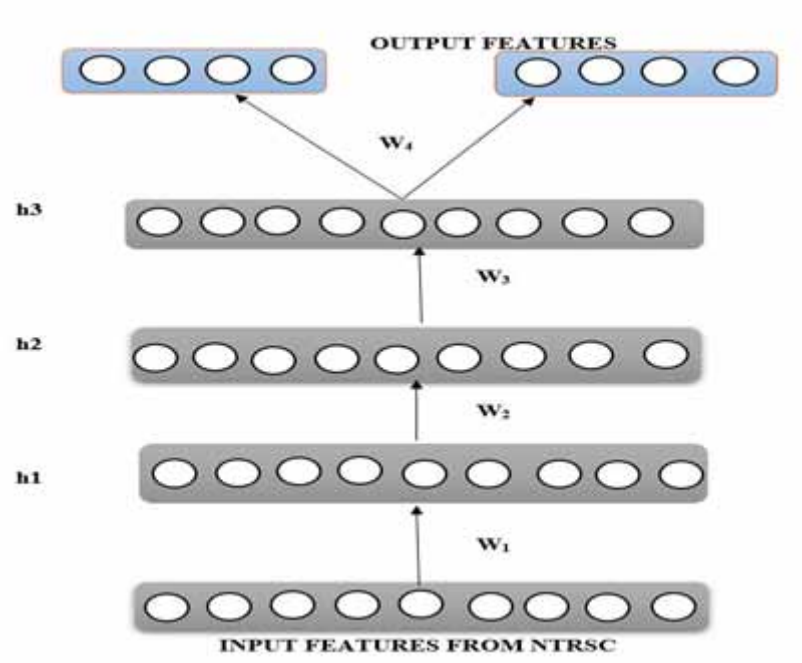
A Deep Neural Network (Dnn) is an Artificial Neural Network (ANN) with several layers in between layer of input and output. Although neural networks can take many different forms, they all have the same fundamental building blocks: axons, synapse, weights, biases, and function. A Deep Neural Network is a collection of neurons organized in many layers, with each layer receiving the preceding layer's neuron activations as input and performing a basic computation. By using mathematical operations based on linear or non-linear relationships, it converts input into output. Every mathematical operation is a layer, and the term "deep" pertains to the network's multiple levels. Deep Neural Networks analyze data in complex ways using advanced mathematical modeling. The network's neurons work together to create a complex arbitrary mapping from input to output. The weights of each neuron are adjusted using a technique called error backpropagation to learn this mapping from the data.

Deep TRS Architecture consists of three sorts of layers in the model. Updated Decision Tables Layer, Deep Rough Decision System layer, and the Novel Deep Tolerance Rough Neural Layer. A deep Tolerance rough system architecture is developed when these levels are stacked (Hassan, 2017).

1. Updated Decision Table Layer – Updated Decision from Novel Tolerance Rough Set Classifier (NTRSC) with input data will be stored in the input layer. It is made up of a series of decision tables.
2. Deep Rough Decision System Layer - The output of the deep rough decision system, which is a decision table that performs a backpropagation function.
3. Novel Deep Tolerance Rough Neural Layer - The Deep Tolerance layer tries to generate predicted classes for the decisions using a standard Deep Neural Network. Figure 4 depicts the Deep Neural Network architecture.

The proposed classification approach is divided into three phases:

Figure 4. Deep neural network architecture



(1) First phase, Novel Tolerance Rough Set Model with inequality constraints is used to construct training decision tables for each sub-decision and compute approximation sets of classes in each decision table; Boundary Region, Upper approximation, and Lower Approximation. Compute the Centroid values and find the minimum distance between the decisions.
(2) In the Second phase, initialize the random weights of Novel Deep Tolerance Rough Neural Network Architecture.
(3) In the Third phase, Classify the decisions into a particular group (class) and it helps to lower the misclassification error rate.

Table 2 depicts a detailed description of each layer and its functions. Figure 5 depicts the overall layout of the proposed Deep TRS Architecture.

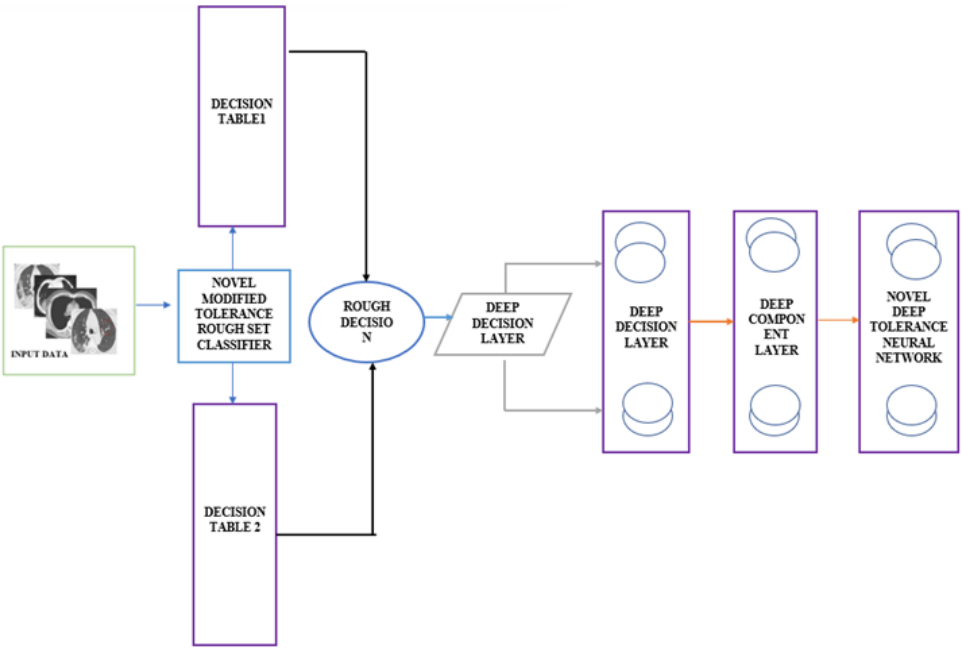
The Algorithm for Deep TRS Architecture is shown in Algorithm 2. The most of Deep Neural Networks (DNNs) are Feed-Forward Neural Networks (FFNNs), in which input is sent from the input to the output layer never moving towards the back and the connections between the levels only go forward and never come into contact with another node. Using a decision from the Novel Tolerance Rough Set Classifier as the input layer in the DTRSA and passing it to the hidden layer. In Step 3, Forward Propagation is used. The activation function receives the weighted aggregate. The activation function determines which nodes are to be used in the feature extraction process. The sixth step is backward propagation. To reduce error, the weights are adjusted and the result is back-propagated. Weights are modified to create an attired Model. The output is compared to the original result by the model. It iteratively improves accuracy by repeating the process.

ALGORITHM 2: NOVEL DEEP TRS ARCHITECTURE -CALL DTRSA (C, D)
INPUT: Updated Decision Table where the conditional attributes set (decision attribute) D = {d_1, d_2, …, d_n}.
OUTPUT: Decision

Table 2. Detailed description of each layer

Name of the Layer	Layer Order	Functions of the Layer	The phase of the Layer
Updated Decision Table Layer	Applied Novel Tolerance Rough Set Algorithm	• Generate Certain rules using the NTRSC approach • Generate Rules for boundary Region • Updated Decision from Novel Tolerance Rough Set Classifier. • Decision 1 – COVID • Decision 2 – NON-COVID	First Phase
Rough Decision System	Second Layer	• Form Together as Rough Decision System	
Deep Rough Decision Table	Input Layer	• Get a Deep decision Table as input for the input Layer	
Deep Decision Layer	First Hidden Layer	• Initializing the Network • Applied Activation Functions • Execute Forward Propagation • Implement optimization Algorithms-Gradient Descent	Second Phase
Deep Component Layer	Second Hidden Layer	• Employ Backward Propagation • Compute chain rule • Update the Parameters.	
Novel Deep Tolerance Neural Network	Output Layer	• Compute the Decision and classify it into COVID or NON-COVID	Third Phase
Activation Functions	Sigmoid	$\frac{1}{1+e^{-x}}$	
Optimization Algorithm	Gradient Descent		

Figure 5. Overall layout of the proposed deep TRS architecture



Step 1: The input layer receives the data and delivers it to the hidden layer. Weights are assigned to each input at random by the connectivity between the two layers.
Step 2: Apply Forward Propagation. To the activation function, the weighted aggregate is passed. The activation function defines which nodes should be used to extract features.
Step 3: Apply Backward Propagation. To minimize error, weights are modified and the output is back-propagated. Modify the weights between neurons to produce a good Model.
Step 4: The output is compared to the original result by the model. To enhance accuracy, it repeats the process.
Step 5: Predict the class label

6. EXPERIMENTAL RESULTS AND DISCUSSION

The Anaconda environment is used to conduct this research. It runs on I5 processor with 8 GB RAM. Windows 11, 64-bit operating system was utilized to simulate the proposed architecture and the benchmark methods are utilized for comparison. The DTRSA Architecture was implemented in Anaconda Software. "Novel Tolerance Rough Set classifiers", "Naïve Bayes-classifier", "K-Nearest Neighbor-Classifier", "Random Forest-Classifier", "Decision Trees-Classifier", and "Support Vector Machine-Classifier" are utilized to compare the performance of the proposed Deep TRS Architecture.

The first step in the classification process is gathering input and output feature pairs and separating them into a learning (training) set and an evaluation (testing) set. To ensure greater consistency between test findings, the cross-validation model was adopted. Performing the study on one subset (training) and assessing the analysis of the other subset are all parts of the cross-validation process. Subsets of a collection of information are harmonized (testing). The testing results are acquired after performing numerous iterations of cross-validation with various divisions to reduce variability. The classification algorithm was examined using the tenfold cross-validation approach. A tenfold cross-validation approach divides the data set into a 9:1 ratio where the dataset is separated into 10 sets total, 9 sets utilized for learning, and 1 set used for validating. Tenfold cross-validation has the benefit of eventually using every sample in the dataset for both training and testing. The results are validated using different validation accuracy measures. The parameter settings are described in Table 3.

The accurateness of the classification algorithm can be evaluated using a variety of evaluation measures. Sensitivity, Specificity, Mathew's Correlation Coefficients (MCC), Error Rate (ER), Balanced Classification Rate (BCR), and additional measures such as Lift, Youden's index are among the metrics that are measured. The percentage of positive testing results that are true positives is known as positive predictive value (correct diagnoses). It is an important indicator of an experimental method's performance since it reflects the likelihood that an actual testing represents the primary situations. The negative predictive value is the percentage of people who test negative but are actually

Table 3. Parameter Setting for Classification Algorithms

CLASSIFIER	PARAMETER SETTING	TEST SIZE
Deep Neural Network	Activation Function: Sigmoid, Learning Rate = 3e-3	Cross-Validation Method-10 Folds (9:1,9 For Training and 1 for Testing)
K-Nearest Neighbour Classifier	K = 5	
Random Forest Classifier	Scoring = "ROC_AUC", Cross-Validation = 10	
Naïve Bayes Classifier	Gaussian Naive Bayes	
Support_Vector_Machine	Linear kernel	

disease free. When the abnormality measure is absent, the negative predictive value is the possibility of an undesirable result. It is defined as the percentage of people who are appropriately diagnosed despite a negative test result. When a test has a high negative predictive value, it suggests that it is more likely to correct its evaluation when it returns a negative result. Some of the important measures are discussed in Table 4. (Bekkar et al., 2013; Sokolova & Lapalme, 2009; Demsar, 2006; Ganesan et al., 2017). Table 5 depicts the results of each benchmark classification with the proposed Deep TRS Architecture in terms of Confusion Matrix, F1-Score, G-Mean etc.,

The proposed Deep TRS Architecture performance analysis and comparative classifiers based on validation measures are summarized in Table 6. The efficiency of the proposed approach as well as many standard approaches based on accuracy measures is visibly depicted in Table 6. It appears that the "Naïve Bayes" provides the least value, while the presented deep TRS architecture outperformed all other approaches for all performance metrics.

Table 4. Detailed interpretation for various classification measures

METRICS	EXPLANATION	FORMULA
Precision	The degree of perfection.	$\frac{TP}{TP+FP}$
Recall (Sensitivity)	To calculate true positive rates.	$\frac{TP}{TP+FP}$
Specificity	Calculate the True negative rates.	$\frac{TN}{TN+FP}$
F1-Score	Precision and recall are combined to form a harmonic mean.	$\frac{PRECISION * RECALL}{PRECISION + RECALL}$
G-Mean	The product of both classes is prediction accuracies.	$\sqrt{PRECISION * RECALL}$
Accuracy	Calculate the true value of the class attributes probability.	$\frac{TP+TN}{TP+TN+FP+FN}$
Error Rate	An approximation of the chance of misclassification.	$\frac{FP+FN}{TP+TN+FP+FN}$
Matthews Correlation Coefficient	The relationship among the predicted and actual class.	$\frac{\left(TP*TN\right)-\left(FP*FN\right)}{\sqrt{\left(TP+FP\right)*\left(TP+FN\right)*\left(TN+FP\right)*\left(TN+FN\right)}}$
Lift	The percentage of outcomes that were obtained with and without the Model.	$\frac{\left(TP\,/\left(TP+FP\right)\right)}{\left(\left(TP+FN\right)/\left(TP+TN+FP+FN\right)\right)}$
Youden's Index	The mathematical average of true positive rate and true negative rate.	$SENSITIVITY + SPECIFICITY - 1$
Balanced Classification Rate (BCR)	The combined mean of true positive rate and true negative rate.	$\frac{1}{2}\left(SENSITIVITY + SPECIFICITY\right)$

Table 5. Comparison of proposed architecture and various benchmark algorithms

GLCM FEATURES	Classification Algorithm	Desired Output	Output Result for Confusion Matrix C N-C		Precision	Recall	F1-Score	Support	G-Mean
GLCM 0°	**DTRSA**	**C**	**326**	**23**	**0.96**	**0.93**	**0.95**	**349**	**0.94**
		N-C	**14**	**383**	**0.94**	**0.96**	**0.95**	**397**	**0.94**
	NTRSC	C	323	26	0.92	0.93	0.92	349	0.92
		NC	29	368	0.93	0.93	0.93	397	0.93
	DTC	C	317	32	0.87	0.91	0.89	349	0.88
		N-C	47	350	0.92	0.88	0.90	397	0.89
	RFC	C	319	30	0.89	0.91	0.90	349	0.89
		N-C	39	358	0.92	0.90	0.91	397	0.90
	NBC	C	238	111	0.84	0.68	0.75	349	0.75
		N-C	47	350	0.76	0.88	0.82	397	0.81
	KNN	C	326	23	0.91	0.93	0.92	349	0.91
		N- C	34	363	0.94	0.91	0.93	397	0.92
	SVM	C	271	78	0.91	0.78	0.84	349	0.84
		N - C	28	369	0.83	0.93	0.87	397	0.87
GLCM 45°	**DTRSA**	**C**	**297**	**52**	**0.84**	**0.84**	**0.86**	**349**	**0.85**
		N-C	**86**	**311**	**0.87**	**0.84**	**0.86**	**397**	**0.85**
	NTRSC	C	294	55	0.81	0.84	0.82	349	0.82
		N-C	71	326	0.86	0.82	0.84	397	0.83
	DT	C	281	68	0.77	0.81	0.79	349	0.78
		N- C	84	313	0.82	0.79	0.80	397	0.80
	RF	C	284	65	0.77	0.81	0.79	349	0.78
		N –C	86	311	0.83	0.78	0.80	397	0.80
	NBC	C	209	140	0.75	0.60	0.66	349	0.67
		N - C	71	326	0.70	0.82	0.76	397	0.75
	KNN	C	291	58	0.79	0.83	0.81	349	0.80
		N - C	79	318	0.85	0.80	0.82	397	0.82
	SVM	C	217	132	0.74	0.62	0.68	349	0.67
		N –C	76	321	0.71	0.81	0.76	397	0.75
GLCM 90°	**DTRSA**	**C**	**340**	**9**	**0.94**	**0.97**	**0.95**	**349**	**0.94**
		N –C	**26**	**371**	**0.98**	**0.93**	**0.95**	**397**	**0.94**
	NTRSC	C	338	11	0.90	0.97	0.93	349	0.93
		N-C	39	358	0.97	0.90	0.93	397	0.93
	DTC	C	291	58	0.85	0.83	0.84	349	0.83
		N - C	53	344	0.86	0.87	0.86	397	0.86
	RFC	C	320	29	0.91	0.92	0.91	349	0.91
		N –C	33	364	0.93	0.92	0.92	397	0.92
	NBC	C	173	176	0.68	0.50	0.57	349	0.58
		N - C	81	316	0.64	0.80	0.71	397	0.71
	KNN	C	325	24	0.89	0.93	0.91	349	0.90
		N - C	42	355	0.94	0.89	0.91	397	0.91
	SVM	C	234	115	0.84	0.67	0.75	349	0.75
		N - C	44	353	0.75	0.89	0.82	397	0.81

continued on following

GLCM FEATURES	Classification Algorithm	Desired Output	Output Result for Confusion Matrix C N-C		Precision	Recall	F1-Score	Support	G-Mean
GLCM 135°	**DTRSA**	**C**	**336**	**13**	**0.95**	**0.96**	**0.95**	**349**	**0.95**
		N –C	**19**	**378**	**0.97**	**0.95**	**0.96**	**397**	**0.95**
	NTRSC	C	322	27	0.90	0.92	0.91	349	0.90
		N-C	35	362	0.93	0.91	0.92	397	0.91
	DTC	C	290	59	0.88	0.83	0.85	349	0.85
		N - C	40	357	0.86	0.90	0.88	397	0.87
	RFC	C	319	30	0.90	0.91	0.91	349	0.90
		N- C	36	361	0.92	0.91	0.92	397	0.91
	NBC	C	210	139	0.73	0.60	0.66	349	0.66
		N- C	79	318	0.70	0.80	0.74	397	0.74
	KNN	C	326	23	0.88	0.93	0.90	349	0.90
		N-C	46	351	0.94	0.88	0.91	397	0.90
	SVM	C	251	98	0.84	0.72	0.77	349	0.77
		N- C	49	348	0.78	0.88	0.83	397	0.82

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The accuracy of the proposed methodology is Deep Tolerance Rough Set Architecture which correctly identified 0.95% of COVID 19 classification data for GLCM 0° features is shown in Table 6. For the GLCM 0° data set, the accuracy of the "Novel Tolerance Rough Set -Classifier", "Decision Tree-Classifier", "Random Forest-Classifier", "Naïve Bayes-Classifier", "K-Nearest Neighbor-Classifier", "Support Vector Machine -Classifier" algorithms are 0.93%,0.89%,0.91%,0.79%,0.92%, and 0.86% respectively.

The accuracy of the proposed methodology is Deep Tolerance Rough Set Architecture which correctly identified 0.86% of COVID 19 classification data for GLCM 45° features is shown in Table 7. For the GLCM 0° data set, the accuracy of the "Novel Tolerance Rough Set -Classifier", "Decision Tree-Classifier", "Random Forest-Classifier", "Naïve Bayes-Classifier", "K-Nearest Neighbor-

Table 6. Comparison of proposed architecture and various benchmark algorithms for GLCM 0°measures

GLCM 0°Measures	DTRSA	NTRS-C	DT-C	RF-C	NB-C	K-NN-C	SVM-C
Accuracy	0.95	0.93	0.89	0.91	0.79	0.92	0.86
Specificity	0.94	0.93	0.91	0.92	0.75	0.94	0.82
Sensitivity	0.95	0.91	0.85	0.89	0.83	0.90	0.90
MCC	0.90	0.85	0.78	0.81	0.57	0.84	0.71
Youden Index	2.89	2.85	2.78	2.81	2.58	2.84	2.72
Lift	2.04	1.96	1.86	1.90	1.78	2.84	1.98
BCR	0.94	0.92	0.89	0.90	0.79	0.92	0.86
Error Rate	0.04	0.07	0.10	0.09	0.21	0.07	0.13

Table 7. Comparison of proposed architecture and various benchmark algorithms for GLCM 45°measures

GLCM 45°Measures	DTRSA	NTRS-C	DT-C	RF-C	NB-C	K-NN-C	SVM-C
Accuracy	0.86	0.83	0.80	0.80	0.72	0.82	0.72
Specificity	0.87	0.80	0.80	0.81	0.69	0.84	0.70
Sensitivity	0.84	0.85	0.76	0.77	0.74	0.78	0.74
MCC	0.72	0.66	0.57	0.59	0.43	0.63	0.43
Youden Index	2.72	2.66	2.57	2.59	2.44	2.63	2.44
Lift	1.81	1.72	1.63	1.64	1.59	1.68	1.58
BCR	0.86	0.83	0.78	0.79	0.72	0.81	0.72
Error Rate	0.13	0.16	0.21	0.20	0.28	0.18	0.27

Classifier", "Support Vector Machine" classifier algorithms are 0.83%,0.80%,0.80%,0.72%,0.82%, and 0.72%, respectively.

The accuracy of the proposed methodology is Deep Tolerance Rough Set Architecture which correctly identified 0.94% of COVID 19 classification data for GLCM 90° features is shown in Table 8. For the GLCM 0° data set, the accuracy of "Novel Tolerance Rough Set -Classifier", "Decision Tree-Classifier", "Random Forest-Classifier", "Naïve Bayes-Classifier", "K-Nearest Neighbor-Classifier", "Support Vector Machine" - Classifier algorithms are 0.93%,0.85%,0.92%,0.66%,0.91%, and 0.79%, respectively.

Table 8. Comparison of proposed architecture and various benchmark algorithms for GLCM 90°measures

GLCM 90°Measures	DTRSA	NTRS-C	DT-C	RF-C	NB-C	K-NN-C	SVM-C
Accuracy	0.94	0.93	0.85	0.92	0.66	0.91	0.79
Specificity	0.93	0.97	0.84	0.92	0.64	0.93	0.75
Sensitivity	0.94	0.89	0.85	0.90	0.68	0.88	0.84
MCC	0.89	0.88	0.70	0.83	0.30	0.82	0.57
Youden Index	2.89	2.86	2.70	2.83	2.32	2.82	2.59
Lift	2.07	1.91	1.80	1.93	1.45	1.89	1.79
BCR	0.94	0.93	0.85	0.91	0.66	0.91	0.79
Error Rate	0.04	0.06	0.14	0.08	0.34	0.08	0.21

The accuracy of the proposed methodology is Deep Tolerance Rough Set Architecture which correctly identified 0.95% of COVID 19 classification data for GLCM 135° features is shown in Table 9. For the GLCM 0° data set, the accuracy of the "Novel Tolerance Rough Set -Classifier", "Decision Tree-Classifier", "Random Forest-Classifier", "Naïve Bayes-Classifier", "K-Nearest Neighbor-Classifier", "Support Vector Machine" are 0.92%,0.87%,0.91%,0.71%,0.91%, and 0.80%, respectively.

The DTRSA produces 95% accuracy and 0.04 error for GLCM- 0°, 0.86% accuracy and 0.13 error rate for GLCM- 45°, 0.95% accuracy and 0.04 error rate for GLCM-90°, 0.95% accuracy and 0.04 error rate for GLCM-135°. The other NTRS-C, DT-C, RF-C, NB-C, K-NN-C and SVM-C error rates of 0.07, 0.10, 0.09, 0.21, 0.07, 0.13 for GLCM- 0°, 0.16, 0.21, 0.20, 0.28, 0.18, 0.27 for GLCM- 45°, 0.06, 0.14, 0.08, 0.34, 0.08, 0.21 for GLCM- 90°, 0.08, 0.13, 0.08, 0.29, 0.09, 0.19 for GLCM- 135° respectively. It is also noted that, the proposed architecture gives more accuracy than other classifiers. Figure 6 and 7 shows the overall accuracy and error rate values of classification algorithms.

Table 9. Comparison of proposed architecture and various benchmark algorithms for GLCM 135°measures

GLCM 135°Measures	DTRSA	NTRS-C	DT-C	RF-C	NB-C	K-NN-C	SVM-C
Accuracy	0.95	0.92	0.87	0.91	0.71	0.91	0.80
Specificity	0.96	0.93	0.85	0.92	0.69	0.93	0.78
Sensitivity	0.94	0.90	0.87	0.89	0.72	0.87	0.83
MCC	0.91	0.83	0.73	0.82	0.41	0.81	0.60
Youden Index	2.91	2.73	2.73	2.82	2.42	2.82	2.61
Lift	2.02	1.92	1.87	1.92	1.55	2.81	1.78
BCR	0.95	0.91	0.86	0.91	0.71	0.90	0.80
Error Rate	0.04	0.08	0.13	0.08	0.29	0.09	0.19

Figure 6. Prediction accuracy

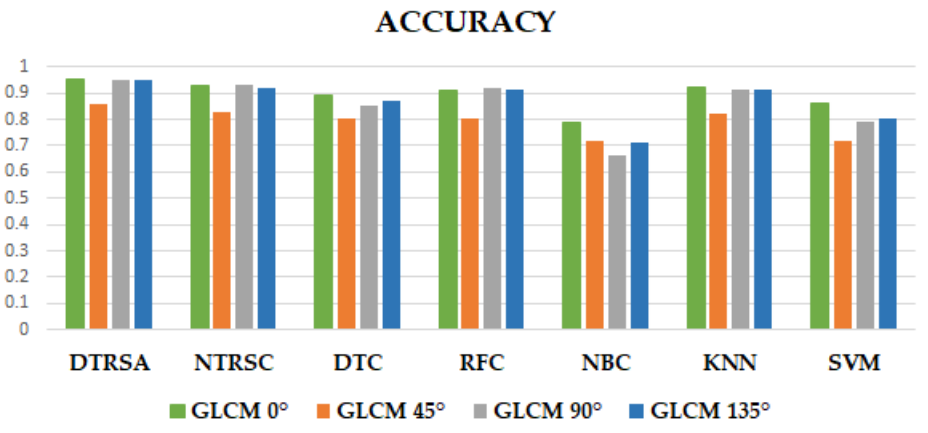
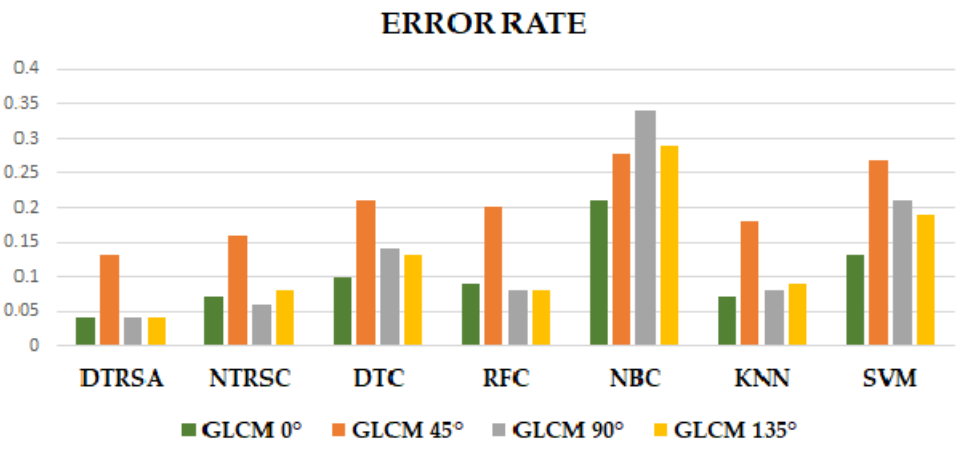


Figure 7. Error rate



6.1 Receiver Operating Characteristic Curve (ROC) Analyses

In clinical epidemiology, ROC analysis is used to measure how well therapeutic diagnostic procedure can differentiate between patient states, generally denoted as "diseased" and "non-diseased" (Swets,1986; Green & Swets, 1966; Metz, 1978). The concept of a "separator" scale, on which the findings for the contaminated and uncontaminated form a pair of overlapping distributions, is the foundation of a ROC curve. A perfectly discriminating test is implied by the total separation of the two underlying distributions, whereas complete overlap implies no discrimination. As the threshold for positivity is changed, the ROC curve depicts the accord among the True Positive (TP) and the False-Positive (FP) (Metz, 1986; Swets,1979; Nivetha & Inbarani, 2022a,b). The plot of FP (1-specificity) versus TP (sensitivity) across several cut-offs produces a ROC curve, which is a curvature in the unit square. In "ROC space," ROC curves equivalent to increasing classifying capabilities of diagnostic tests are gradually closer to the top upper hand quadrant. A ROC curve that is on the diagonally lines represent the outcome of a clinical diagnosis that is not worse than random, i.e., a test that yields positive or negative findings irrelevant to the actual illness condition. The slope of a ROC curve at any point is equal to the ratio of the two-distribution function explaining the dispersion of the separator parameter in the diseased and non-diseased peoples, respectively (Greiner et al., 2000; Choi, 1998; Zhu et al., 2022; Yousefirizi, et al., 2022) . The likelihood ratio of the two density functions defining the distribution of the separator variable in the sick and non-sick populations. Figures 8-11 reveal the ROC curve analysis for GLCM- 0° dataset, GLCM- 45° dataset, GLCM- 90° dataset, and GLCM- 135° dataset.

7. CONCLUSION AND FUTURE ASPECTS

COVID-19 is a worldwide pandemic. As a result, reducing the transmission rate of the virus is the most effective strategy to stop it. The virus can only be eliminated by initial discovery and therapy. This research aims to quickly diagnose diseases brought on by the COVID-19 virus. To stop the virus from spreading, it's vital to diagnose these disorders as soon as possible so that the right therapy can be put in place and COVID-19 patients can be isolated. This research implements the Deep TRS Architecture learning model for detecting COVID-19, i.e., COVID and NON-COVID images from CT scan images. The experimental result shows that 0.95% accuracy and 0.04% error for GLCM-0°, 0.86% accurateness and 0.13% fault percentage for GLCM- 45°,0.94% accurateness and 0.04% fault percentage for GLCM-90°,0.95% accurateness and 0.04% fault percentage for GLCM- 135°.

Figure 8. ROC for GLCM 0°

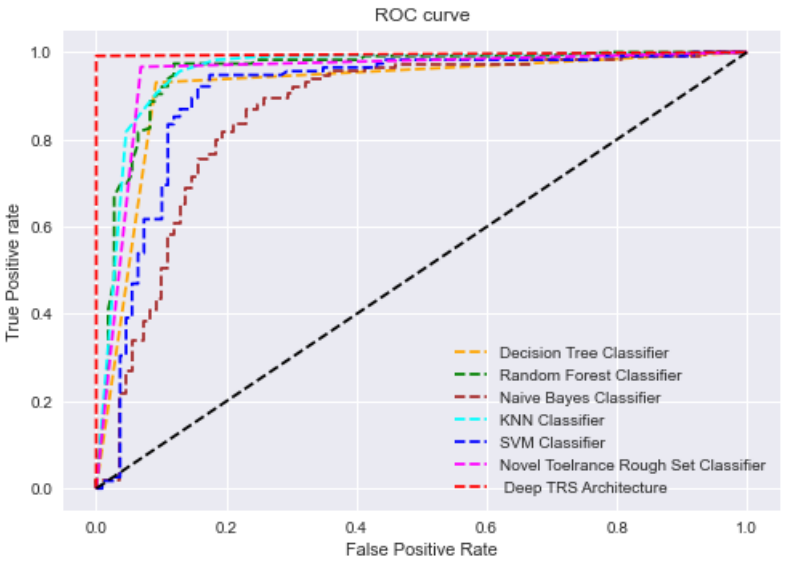
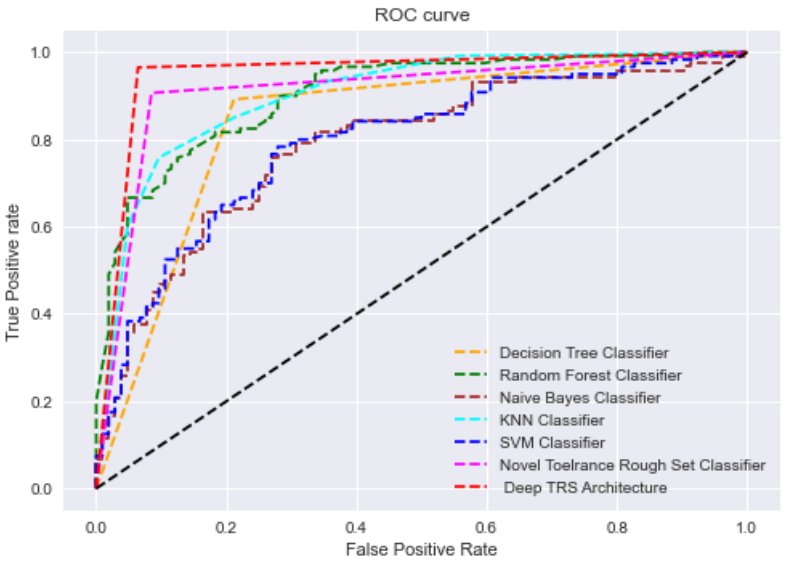


Figure 9. ROC for GLCM 45°



Therefore, the experiments provide successful results in CT imaging modality images. Various experiments were conducted to evaluate the suggested architecture performance, and the outcomes are assessed to standard classification algorithms. A long list of validation measures has been used to compare several techniques: Matthews Coefficient Correlation, Precision, Recall, Specificity, G-Mean, Error Rate, F-Measure, Balanced Classification Rate, and Youden's Index are used to assess these techniques. The experiments proved that the Deep TRS Architecture was the most effective one for the COVID-19 CT scan image classification. The proposed system can be hybridized with metaheuristic optimization techniques as a future direction of this study in addition to proposing other DL networks.

Figure 10. ROC for GLCM 90°

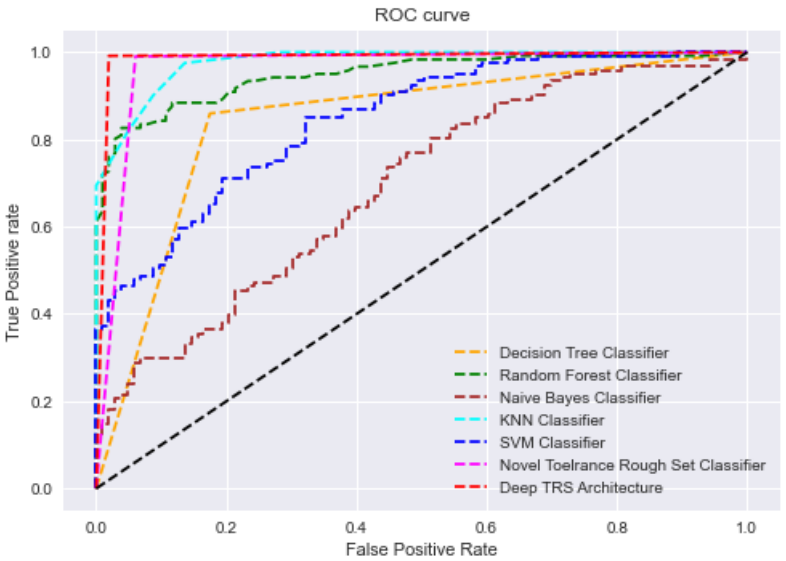
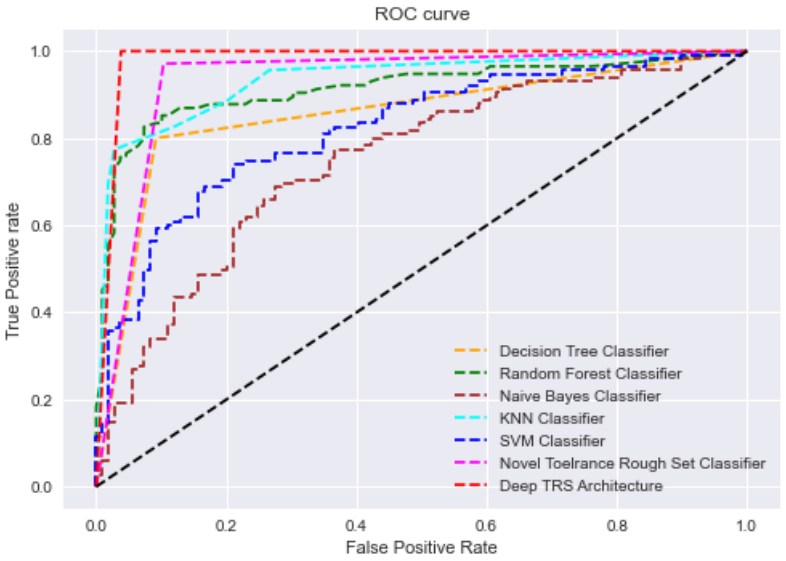


Figure 11. ROC for GLCM 135°



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