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CT image-based COVID-19 diagnosis and severity determination

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Abstract

Because it can reveal the internal architecture of previously invisible human body regions, medical image processing has attracted a lot of attention for use in medical diagnostics. Lung and brain illness has emerged as one of the major medical concerns of our day. At the early period of pregnancy, the difficult challenge is determining the fetal lung's maturity level. During pregnancy, tracking the fetus's growth inside the mother's womb is an essential responsibility. Using image registration and classification techniques, this study effort presents an effective and automated computer-aided methodology for brain tumor detection and segmentation. The following components make up this suggested work: segmentation, classification, contourlet transform, and feature extraction with feature normalization. Adaptive Neuro Fuzzy Inference System (ANFIS) classification approach is utilized to categorize the features for brain Magnetic Resonance Imaging (MRI) tumor segmentation and detection after the retrieved features are optimized using Genetic Algorithm (GA). The suggested methodology for brain tumor detection is assessed quantitatively utilizing the Dice similarity coefficient, segmentation accuracy, precision, sensitivity, and specificity. Additionally, this research effort suggests a productive method for creating a framework for the detection of brain tumors utilizing a fusion-based categorization methodology. The internal low resolution border pixels are improved by fusing the brain MRI images from the public dataset. In order to acquire the non-linear coefficient metric patterns, the merged brain picture is now subjected to the Curvelet transform. In order to distinguish brain images impacted by tumors from brain images unaffected by tumors, features are then generated from these altered non-linear coefficient metric patterns and subsequently classified using the suggested Extreme Learning Adaboost Classification (ELAC) algorithm. The morphological segmentation approach is also used in this work to segment the tumor regions in brain MRI images that have been classified as tumors.

Keywords: Magnetic resonance imaging, classification techniques

Introduction

Acute respiratory distress syndrome (ARDS), pneumonia, and other potentially fatal conditions can result from COVID-19. Therefore, prompt identification and evaluation of the condition's severity and prognosis are crucial for obtaining life-saving interventions including ventilator support and intensive care unit care. When identifying and evaluating the severity of COVID-19 patients, CT imaging is quite beneficial.

The objective is to classify positive instances as High, Moderate, or Low severity after first diagnosing the CT scan for COVID-19 detection. The life risk rate can be decreased by quickly identifying and providing extra care for patients who pose a greater risk. Two approaches are put forward here to do this. Both works use a step-by-step architecture to determine the COVID-19 patients' severity. The first study looked into the ability of an artificial neural network to diagnose COVID-19 and the feature extraction of several pre-trained networks. For the purpose of COVID-19 severity identification, the impact of merging image characteristics and clinical data with well-known classifiers is investigated.

The second study investigated the impact of image features with ANN to detect the severity of COVID-19 and the data augmentation using various pre-trained networks for the COVID-19 diagnosis.

COVID-19 diagnosis and severity detection using clinical data: This article describes a two-step process for identifying the COVID-19 infection from the lung CT scans and estimating the patient's sickness severity. Pre-trained models are utilized to extract the features, and through analysis, the features of AlexNet, DenseNet-201, and ResNet-50 are combined. In order to detect COVID-19, an ANN model is used. Severity detection follows the identification of the COVID-19 infection. Cubic SVM is used to classify the picture features as High, Moderate, or Low after combining them with the clinical data.

Dataset

Furthermore, the metadata from the patient's CT scans is required for the COVID-19 Severity detection. Thus, two openly accessible data sets that have been thoroughly demonstrated are employed here.

Positive and negative data are included in the SARS-CoV-2 CT-scan dataset, which was gathered from both male and female subjects. There are 2482 CT scans in the data set; 1252 of the pictures are positive and 1230 are negative. There is no set size for the photos.

COVID-CT dataset

The photos of COVID-19-infected patients were taken from hospitals and extracted from scholarly journals by the authors using PyMuPDF software (Zhao *et al*., 2020) [6]. The following metadata were manually retrieved and linked to every image: the patient's age, gender, location, medical history, scan duration, COVID-19 severity, and medical report. There are 463 CT pictures that are not COVID-19 and 349 COVID-19 images in the data set. However, the non-COVID pictures show different lung

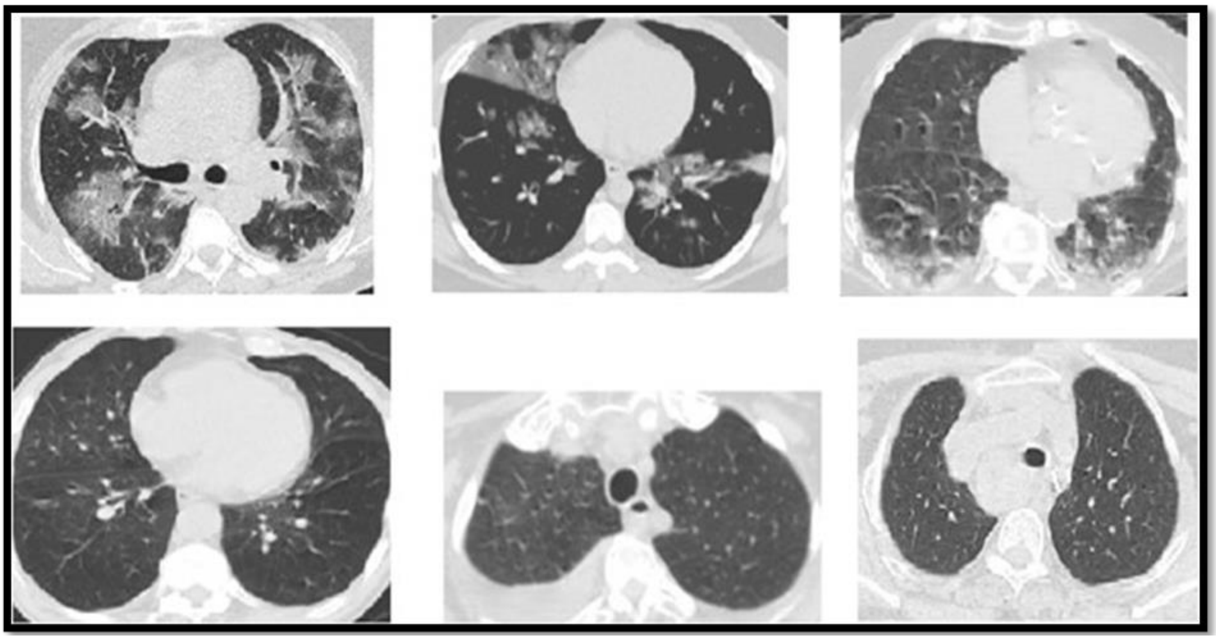

Fig 1: Examples of CT COVID-19 images (positive cases top row) (negative cases bottom row) from the sars-cov-2 CT-scan dataset.

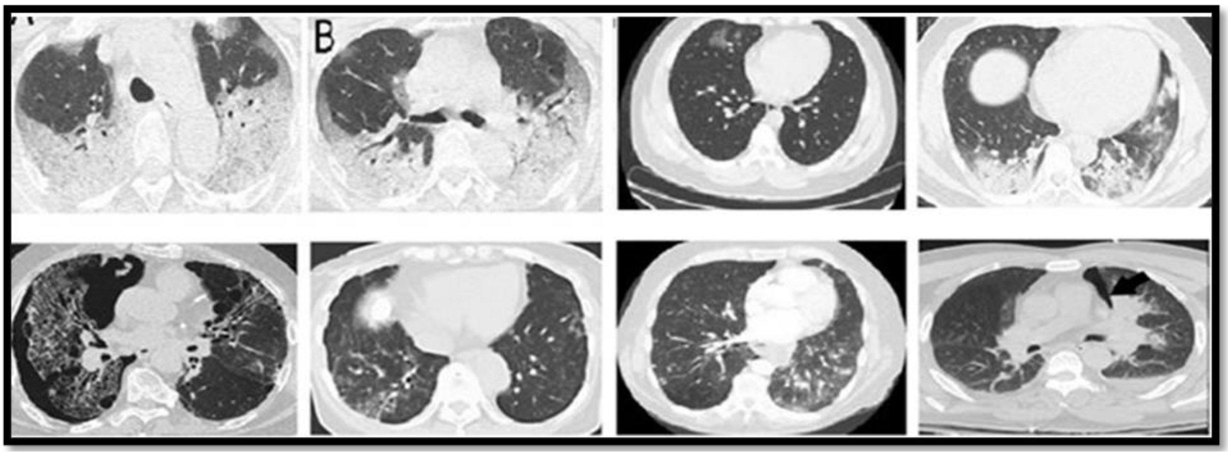

Fig 2: Examples of CT COVID-19 images (positive cases top row) (negative cases bottom row) from the COVID-CT dataset

There are 32 attributes in this dataset. Out of which, nine symptoms are selected in accordance with World Health Organization criteria. The features of fever, tiredness, dry cough, difficulty breathing, sore throat, pains, nasal congestion, runny nose, and diarrhea are utilized to predict the severity using clinical data and CT scans.

This study aims to differentiate COVID-19 infection from other lung infected/normal cases, and then use the features of the image and clinically meaningful symptoms to determine the infection's severity. The data collection contains a large number of non-COVID COVID-CT pictures, making it difficult to determine whether the lung is infected with COVID-19 or another infection. For applications involving picture categorization, feature extraction is crucial. Currently, CNN outperforms all other statistical feature extraction techniques in terms of color, texture, and intensity representation of the visual features. Pre-trained networks are useful for feature extraction in the context of medical imaging. Transfer learning of the previously trained here in the first phase.

To determine whether COVID-19 infects the lung, three networks are used: AlexNet, DenseNet-201, and ResNet-50.

The COVID-19 is predicted by extracting, combining, and training the characteristics in an ANN. After it has been identified, the symptoms and visual aspects are used to determine its severity. Here, three severity levels-High, Moderate, and Low-are taken into account.

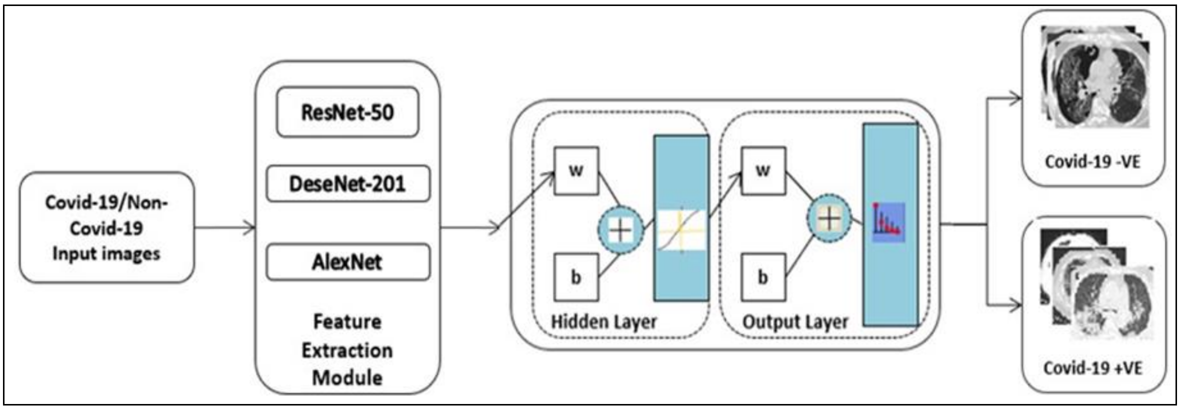

Fig 3: Architecture of the proposed system

Preprocessing

Images with a range of bit depths and sizes make up the data set. Convert each image to the input size and bit depth of the relevant pre-trained network before entering it into a different pre-trained network.

COVID-19 Diagnosis

A branch of machine learning called "Deep Learning" uses computational models inspired by the way the Brain and lung reacts to outside stimuli. The various level features are extracted from the input using a multitude of convolutional filters. Every layer has a distinct number of filters, a different kernel size, and a separate feature set that each filter learns. Use the pre-trained models without the final fully connected layer to obtain distinct feature maps. merged features from ResNet-50, DenseNet-201, and AlexNet in this work. The most pertinent elements are combined, and each image is given a size of 3000. To determine if the CT scan is normal or infected with COVID-19, these features are fed into a neural network. 70% of the data are used for training, 15% are used for validation, and 15% are used for testing.

AlexNet, which can input images up to 224 by 224 pixels, took first place in the 2012 ImageNet competition. There are eight layers in all, three fully connected layers and five convolutional layers. The ReLU activation function was initially implemented by AlexNet, which will lengthen the network's training period. DenseNet-201 is a 201-layered architecture where each layer is feedforward coupled to all subsequent layers. As a result, this network acquires collectively more advanced features. The faults are easily spread backwards because each layer is connected. ResNet-50, a 50-layer CNN architecture with skip connections, was created by He and colleagues. ResNet-50 uses the residual blocks to solve the vanishing gradient problem. Take the features from the fully connected layers that show up before the softmax layer in order to employ a pre-trained model as a feature extractor. The ResNet-50 architecture's "fc1000," the DenseNet-201 architecture's "fc1000," and the AlexNet architecture's "fc8" are where the features are taken from in this instance.

A neural network architecture with three layers is used for the categorization. The input layer contains 3000 neurons, the hidden layer contains 20 hidden neurons, and the output layer contains 2 neurons. The sigmoid activation function is applied in this case. Another name for it is a logistic function, and it maps the input value from 0.0 to 1.0. For weight learning, the back-propagation method is employed. Weights are changed in the direction of the steepest descent in a typical back-propagation algorithm, however this does not ensure faster convergence. This work uses the scaled conjugate algorithm, which removes the requirement for a line search in every iteration.

COVID-19 severity detection

Determining the severity of COVID-19 is a critical first step in providing patients with life-saving care and preserving their lives. In this study, the patient's severe condition was determined using clinical data and CT image features. 169 low severity CT scans, 94 moderate severity images, and 86 high severity images make up the data set (Zhao *et al*., 2020) [6]. A few example pictures are displayed in Figure-4. It is evident from the image itself that it is challenging to identify the severity range. Based on clinical data, Suma *et al*. conducted a study to assess the severity of patients' conditions (Suma *et al*., 2020). Determined the most significant features of this work. In order to determine severity, the clinical data was selected and the retrieved picture attributes were applied.

The severity detection system's intricate architecture is depicted in Figure 5. To determine the severity, characteristics that have been retrieved from AlexNet, DenseNet-201, and ResNet-50 are utilized. The relevant clinical data is combined with these features for every CT scan to create a feature vector with a size of 3009. The classification is then carried out by feeding the cubic SVM with these features and the ground truth. A popular supervised machine learning approach for locating a hyperplane with a wide marginal width is the Support Vector Machine (SVM). If the problems are nonlinear, use distinct kernel functions to solve them. To enable classification, the kernel function often converts the training set of data into a higher-dimensional space. Several kernel functions were tested for this work, however cubic SVM yielded superior outcomes.

The cubic kernel can be represented as
$k(x, y) = (1 + xy)^3$ …………(1)

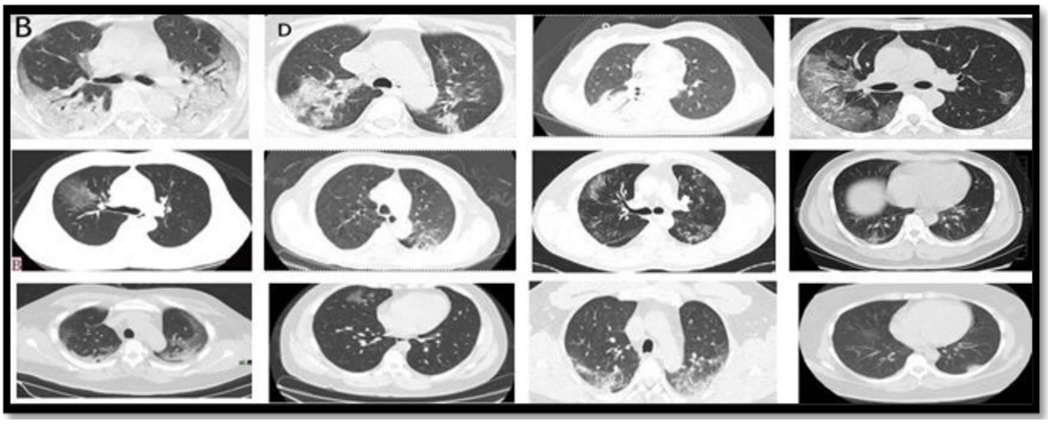

Fig 4: High Severity (Top Row), Moderate Severity (Middle Row), Low Severity (Bottom Row)

Experimental Setup
In MATLAB R2020a, the experiments were conducted. In order to conduct experiments for COVID-19 diagnosis and severity identification, MATLAB R2020a was utilized on a workstation equipped with an Intel Xeon W-2155 3.30 GHz processor, 64 GB RAM, an Nvidia Quadro P-1000 4GB GPU, and Windows 10 operating system.

Results and Discussion: Sensitivity, Specificity, Accuracy, and F1-Score are the metrics utilized to evaluate the system because the primary goal of this work is to determine the severe condition of the patients.

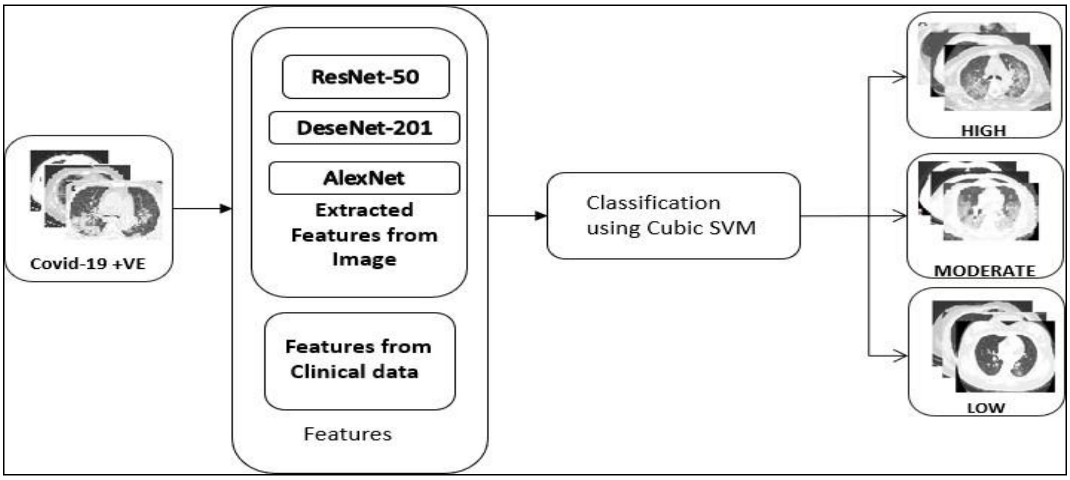

Fig 5: Architecture of the Severity Detection System

Determined the performance metrics for COVID-19 detection and severity in order to conduct the analysis.
Particulars: It can be computed as follows and is defined as the ratio of true negatives (the classifier returned) to total negatives.

$$Specificity = \frac{TN}{TN + FP} \quad \text{…………(2)}$$

Sensitivity can be computed as follows: It is the ratio of true positives to all actual positives.

$$Sensitivity = \frac{TP}{TP + FN} \quad \text{…………(3)}$$

Accuracy: The accuracy indicates the classifier's recognition rate. It can be computed as follows and is defined as the classifier's ratio of accurate predictions to all input data:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{………(4)}$$

The F1-score is an additional metric that evaluates a classifier's utility by taking into account both recall and precision. The weighted average of recall and precision is known as the F1-score. When there is an unequal distribution of classes, this measure is more beneficial. The classification algorithm's predictive power increases with a greater F1-score. It is calculable as:

$$F1\_score = 2 * \frac{precision * recall}{precision + recall} \quad \text{…………(5)}$$

COVID-19 Diagnosis

Table 1: Results Obtained from The Proposed COVID-19 Diagnosis Method

Pre-trained Networks	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	F1 Score (%)
AlexNet+DenseNet-201+ ResNet-50	96.0	88.7	87.3	**92.0**	91.44
DenseNet-201+ResNet-50	89.8	90.5	88.0	90.2	88.89
AlexNet+DenseNet-201	87.5	91.1	90.7	89.3	89.07
DenseNet-201	85.7	88.9	85.7	87.5	85.70
ResNet-50	81.4	92.5	92.3	86.8	86.50
AlexNet	80.4	90.2	85.7	84.82	82.96
MobileNetV2	80.0	88.7	85.10	84.82	82.47

Features taken from different pre-trained models were analyzed in order to determine which pre-trained models were the best. Xception, GoogleNet, and ResNet-18 are three of the pre-trained models whose combinations are examined. Table 1 displays the accuracy of the COVID-19 diagnostic that was made. Through analysis of the data, it is discovered that feeding a classifier features from a single pre-trained model does not produce good results. DenseNet-201 yielded an accuracy of 87.5%, AlexNet yielded an accuracy of 84.2%, while ResNet-50 alone produced an accuracy of 86.8%. Combining the attributes of these models yielded an accuracy of 92.0%.

Table 2: Accuracy Evaluation of The Network with Different Hidden Layer Neurons

Number of Hidden Layer Neurons	Validation (%)	Testing (%)
10	87.21	90.3
15	89.66	91.3
20	93.17	92.0

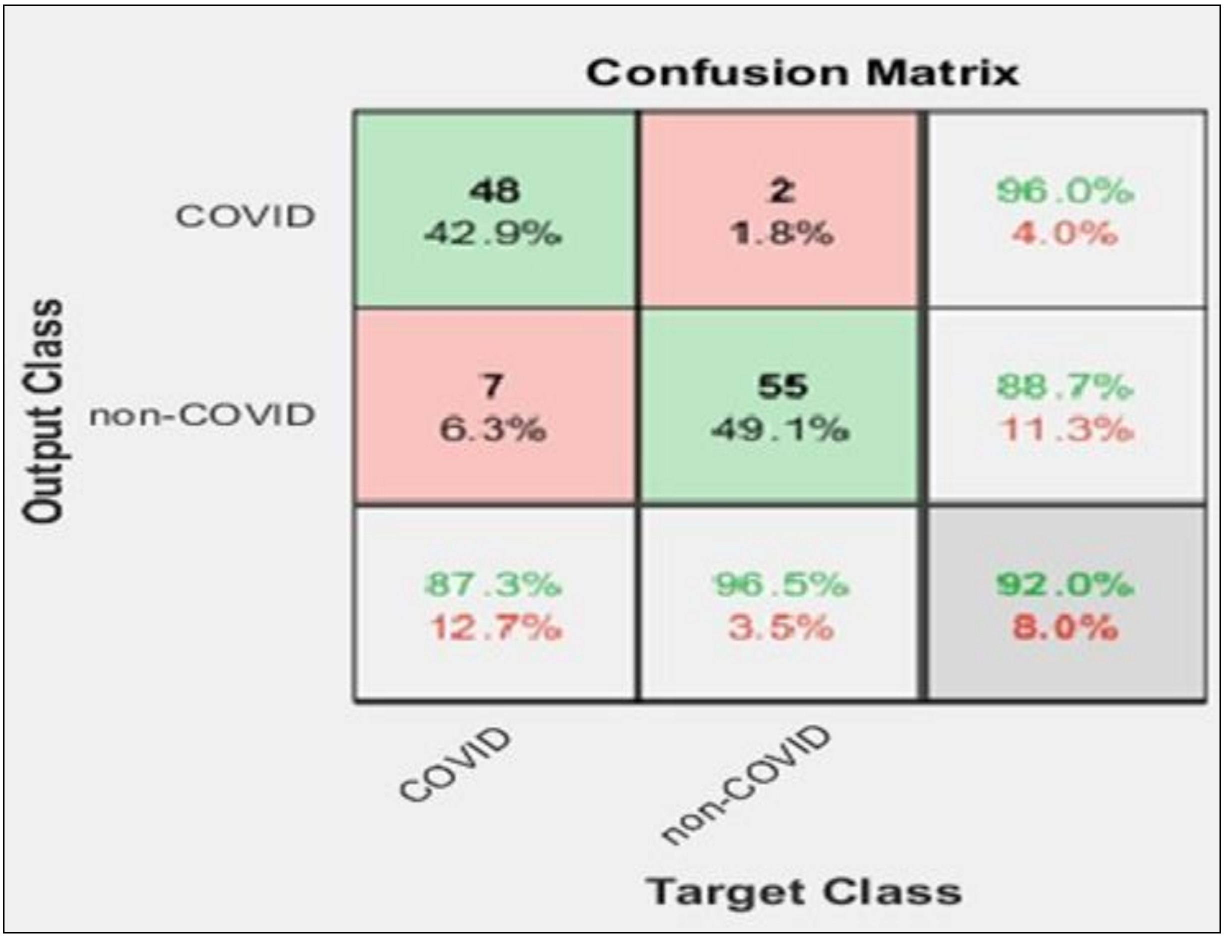

Fig 6: Confusion matrix for the COVID-19 detection

Different neurons in the hidden layer and epochs were used to train the artificial neural network. Table displays the analysis. It is evident from the table that hidden node 20 was producing superior outcomes. When there are more than 20 buried neurons, the results become unsatisfactory. Thus, 20 buried layer neurons were selected. The resulting confusion matrix is shown in Figure. The suggested work is contrasted with other cutting-edge methods that have been documented in the literature in Table.

Table 3: Evaluation of COVID-19 detection system with different state-of-the-art methods

Work	Approach	Sensitivity (%)	Specificity (%)	Accuracy (%)	F1 Score (%)
Liu *et al.*	VGG16 based lesion attention DNN, (Liu, Bin *et al.*, 2020) [2]	88.80	NA	88.60	87.9
Wang *et al.*	UNet, (Wang, Xinggang *et al.*, 2020) [12]	90.70	91.1	90.10	NA
Xu *et al.*	UNet 3D Deep Architecture (Xu, Xiaowei *et al.*, 2020)	86.7%	NA	86.7	NA
Zhang *et al.*	Multi-tasking Seven layer architecture with stochastic pooling (Zhang *et al.*, 2020)	94.44	NA	94.03	NA
Wu *et al.*	Make use of axial, coronal, sagittal views (Wu, Xiangjun *et al.*, 2020)	81.1	NA	76	NA
He *et al.*	Self-supervised learning with transfer learning, DenseNet-201 (He, Xuehai *et al.*, 2020)	NA	NA	86	85
Mantas *et al.*	Auto machine learning platforms (Mantas *et al.*, 2020)	88.31	NA	NA	NA
Proposed	Alex Net + Dense Net 201 + ResNet-50 + ANN [Proposed Work]	96.0	88.7	92.0	91.44

With their lesion attention-based deep neural network technique, Liu *et al*. achieved an accuracy of 88.6% (Liu *et al*., 2020a) [2]. Wang and colleagues employed deep architecture to analyze the 3D CT volumes, achieving a 90.1% accuracy rate (Wang *et al*., 2020b) [12]. With an accuracy of 86.7%, Xu *et al*. Zhang and colleagues achieved a 94% accuracy rate using a proprietary dataset (Xu *et al*., 2020). Using a proprietary dataset, obtained a 76% accuracy rate (Wu *et al*., 2020). The correctness of the work that He *et al*. proposed was 86% (He *et al*., 2020). Using the same data set, Mantas *et al*. obtained a sensitivity of 88.31% (Mantas *et al*., 2020).

COVID-19 severity detection: The majority of the described works focus on identifying the binary severity condition. That can be classified as serious or not. Three severity classes are taken into account in this work. Examined the effectiveness of several classifiers in order to determine the severity based on the combined features. The performance analysis of several classifiers is presented in Table.

Table 4: Accuracy evaluation of different classifier for severity detection

Classifier	Accuracy (%)
Linear SVM	73.3
Naive bayes classifier	67.5
Ensemble Classifier	88.4
Naive bayes classifier with Gaussian Kernel	80.2
Tree based	85.1
KNN	77.6
Cubic SVM	90.0

This indicates that the SVM using the cubic kernel is producing superior outcomes. The accuracy provided by the ensemble classifier is 88.4%. The suggested approach produced a decent classification accuracy; Figure displays the confusion matrix. The test photos were randomly captured. Class 1 represents high severity, Class 2 represents moderate severity, and Class 3 represents low severity. Table presents the findings from the suggested COVID-19 severity detection approach for three classes.

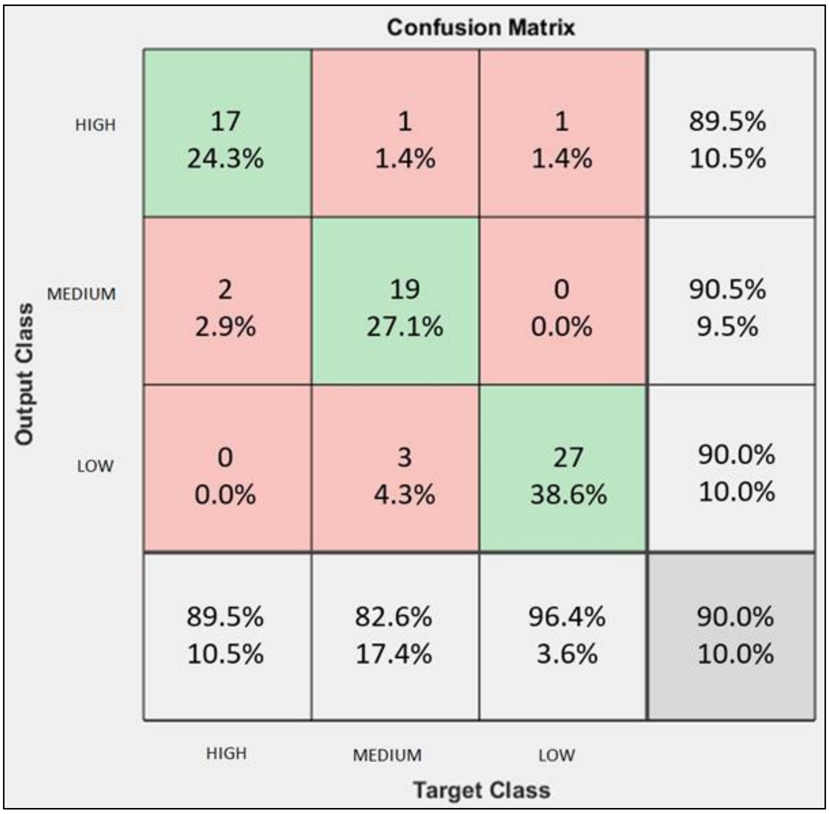

Fig 7: Confusion matrix for the COVID-19 severity detection

Table 5: Results obtained from the proposed COVID-19 severity detection method for three classes

Classes	Sensitivity (%)	Specificity (%)	Precision (%)
High Severity	89.5	96.07	89.5
Moderate Severity	90.5	82.6	91.84
Low Severity	90.0	96.4	97.5

Table 6: Evaluation of the proposed severity detection method with other methods

Work	Performance metric	Value
Chaganti *et al*. Lung Infection	Pearson Correlation Coefficient	0.92 for Percentage of Opacity (p<0.001)
Shen *et al*. Severe Non Severe	Pearson Correlation Coefficient	r ranged from 0.7679 to 0.837, p<0.05
Xiao *et al*. Severe Non Severe	Precision AUC	81.3% 98.7%
Shan *et al*. quatifying the Infection regions	Dice Similarity Coefficient	91.6% 10.0
Pu *et al*. Severity and Progression	Sensitivity Specificity	95% 84%
Tang *et al*. Severe Non Severe	Accuracy	87.5%
Proposed Method (HGH, moderate, Low)	Accuracy	90.0%

For the most part, the studies concentrate on binary classification. Various writers employed varying assessment techniques to determine the extent of the lung infection. Using Dense-UNet architecture with anisotropic kernels, Chaganti *et al*. divided the affected lung regions (Chaganti *et al*., 2020). He assessed the severity using the Pearson correlation coefficient. Pu *et al*. suggested a UNet-based technique for lung border and infected area segmentation (Pu *et al*., 2020). There are 120 more volumes and 72 COVID-19 in the collection. His results showed 84% specificity and 95% sensitivity. Shen *et al*. proposed an adaptive region expanding of the lung segmentation volume (Shen *et al*., 2020). The Pearson correlation coefficient was employed in this instance as well to assess the performance. The data set used for the investigation included the CT scans of 44 patients. Xiao *et al*. used the ResNet-34 architecture to construct a solution for binary severity prediction (Xiao *et al*., 2020). With 23,812 pictures, he obtained an 81.3% accuracy value. Shan *et al*. investigated VB-Net and determined the severity using the Dice similarity coefficient (Shan *et al*., 2020).The machine learning algorithm's potential was investigated by Tang *et al*. Using 176 patients' chest CT scans, he achieved an accuracy of 87.5% (Tang *et al*., 2020). The suggested approach achieved an accuracy of 90.0% overall while taking into account the three severity levels.

Conclusion

The purpose of the planned study is to determine if an individual has COVID-19 and evaluate the severity of the patient's condition so that the medical team can arrange for the necessary facilities-such as a ventilator and oxygen-ahead of time. 349 COVID-19 photos with the information needed to estimate each patient's severe condition are included in the (Zhao *et al*., 2020) [6]. Taking into account the data sets from Zhao *et al*. (2020) [6] a fully autonomous system was constructed. Samples that test positive for COVID-19 are chosen from (Zhao *et al*., 2020) [6] since the metadata pertaining to the COVID-19 severity is available there. 60% of positive data with random selection for testing, encompassing conditions of high, medium, and low severity. Augmentation is used on the remaining data to obtain a large number of samples. RandXscale was employed in the range of 0.8 to 1.2, shear in the range of -20 to 20, and rotation in the range of -30 to 30 for data augmentation. Don't apply any augmentation for non-COVID photos.

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