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# Enhancing COVID-19 Diagnosis and Severity Evaluation through Machine Learning Algorithms Applied to CT Images

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**Abstract:**There are still many important obstacles that make evaluating COVID-19 as a pandemic difficult. Utilising all of the tools and resources available in the field is essential to overcoming these obstacles. Although RT-PCR, a method that is commonly employed, is excellent in detecting the presence of viruses, its ability to determine the severity of an illness is still limited. This work presents a reliable and effective automated approach that uses CT scan images to stratify COVID-19 severity into three different categories are mild, moderate, and severe. Three types of parameters are extracted in order to carry out the categorization process: infection ratio, statistical texture features, and GLCM/GLRLM texture features. Using a simple segmentation strategy, we achieve accurate scan categorization by applying four different traditional methods like a DT, NB, SVM, and KNN. Four essential phases are included in our suggested model: preprocessing, feature extraction, classification, and performance assessment. using SVM yields impressive segmentation accuracy of 99.12% for normal, 98.24% for mild, 98.73% for moderate, and 99.9% for severe COVID-19 infection. The model outperforms previous models with an amazing AUC of 0.99. This development is expected to improve diagnostic accuracy, facilitate faster evaluation of infection stage, and guarantee prompt, customised therapy delivery by medical practitioners.

**Keywords:** CT-Scan, Covid-19, Infection ratio, Statistical texture feature, SVM, KNN, Segmentation, NB, DT etc.

## I. INTRODUCTION

Global effects have been felt since the SARS-CoV-2 which produced the COVID-19 virus first surfaced in December 2019. Echoing past pandemics like Middle and East respiratory disease (MERS) severe acute respiratory syndrome (SARS), this outbreak quickly precipitated a major international health emergency [1]. In Mar 2020, the WHO formally designated COVID-19 as a community health emergency, acknowledging its significant social and health ramifications.

COVID-19 is a virus that causes more than just cough, weariness, respiratory discomfort, and sore throat. By May 5, 2022, there will have been more than 6.2 million verified cases and deaths linked to the virus. It has had a profoundly transforming effect on economies, cultural norms, educational systems, and global well-being [2]. Typical signs of COVID-19 include cough, fatigue, infection, breathing problems, and sore throat, although other less common symptoms have also been reported. The effects of the pandemic extend beyond public health, affecting various aspects of society, including social dynamics, the economy, education, and overall well-being [3].

Although the most common procedure for identifying COVID-19 is RT-PCR, its early limitations during the pandemic led to a sharp increase in the use of CT scans. These scans were an additional resource, providing deeper insights and helping to detect the infection early in afflicted people. These scans demonstrated increased sensitivity in identifying COVID-19 infections, particularly early on when RT-PCR encountered difficulties [4-6].

CT scans have become essential diagnostic tools because they offer detailed in-formation on the existence and severity of infections. These scans provide a de-tailed picture of the severity and development of the disease by identifying distinctive lung alterations associated with COVID-19, such as ground-glass opacities and lung fibrosis, using non-invasive imaging technologies [7-8].

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Our main goal in this research project is to create a highly accurate and advanced forecasting system. Employing cutting-edge machine-learning methodologies, this technology harnesses CT scan imagery to precisely gauge the extent of COVID-19 infection, providing a comprehensive assessment of severity with remarkable accuracy. Our objective is to efficiently classify infection severity into three separate stages: severe, moderate, and mild [9,10]. To do this, we use sophisticated segmentation algorithms to extract important factors including infection ratio and textural qualities. In order to verify and improve our suggested model, a large dataset consisting of different CT scans with different levels of illness severity is being used. By taking an all-encompassing approach, we hope to further the creation of reliable diagnostic instruments and improve our comprehension and handling of COVID-19's effects on public health and treatment strategies [11, 12, 13, 14].

## *A.Machine learning*

Prevention of disease mask wearing, sanitizing, social distancing, and maintaining the ecosystem is crucial for containing viral spread. Technology continues to show a critical role in the early detection of the infection. Machine learning, in particular, has demonstrated its capabilities in a variety of medical fields. The focus of machine learning is developing methods that enable system to learn on their own without explicit programming instructions, which will transform the field of virus detection and diagnosis. ML classifiers offer advantages such as quick identification of trends and patterns, automation, continuous improvement, handling complex data, and applicability across different domains.

Supervised Learning (SL) involves training the computer using input and output data to establish relationships and patterns, enabling it to envisage novel data outcomes. Applications like categorization and recognition heavily rely on SL. Unsupervised Learning (USL) trains the computer with input data only, without providing output data, to identify inherent relationships and patterns within the data and make predictions about new data outputs. Collecting is a notable application of USL. Reinforcement Learning (RL), unlike SL, is a self-learning system that learns through trial and error without explicit output data. Autonomous cars are an example of an RL application. The goal of this work is to build a strong framework for the identification and examination of the severity of COVID-19 infections using CT scans by utilizing the power of supervised learning (SL) techniques in the field of machine learning. Developing a robust classification scheme that divides COVID-19 instances into three categories moderate, severe, and mild is our main goal. In order to improve classification accuracy and diagnostic precision, this involves training the algorithm using a variety of dataset that includes CT images labeled with relevant severity descriptors. The suggested system includes a number of SL approaches for precise and automated categorization, including traditional algorithms. Integrating ML into the medical field holds immense potential for improving disease diagnosis and management, leading to better healthcare outcomes [15, 16, 17, 18, 19].

## *B.Our Research Contribution*

**OUR RESEARCH AIMS TO CONTRIBUTE SIGNIFICANTLY TO THE FIELD OF COVID-19 DIAGNOSIS UTILIZING CT SCANS. WE HAVE SEVERAL OBJECTIVES FOR OUR RESEARCH STUDY:**

1) Developing Accurate Detection Technique: Our objective is to develop a simple yet accurate approach for CT scan-based assessment of COVID-19 infection rigor. We want to improve the competency and precision of the diagnosis process by implementing cutting-edge machine-learning techniques.
2) Four Stage Classification: Severe, Mild, Normal, and Moderate are the four levels we attempt to divide CT scans into depending on the CT findings and supporting explanation files that are included in the dataset

this categorization will be made. It gives insightful information about the severity of the illness, permitting proper treatment choices. The study use quartet of machine learning (ML) models, including Decision Trees (DT), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) and Naive Bayes, which are four well-known and efficient ML models. By leveraging the strengths of each algorithm, we can achieve robust and accurate classification results.

3) Feature Extraction: The foundation of our analysis from CT images is the extraction of important statistical texture features like mean, skewness, kurtosis, and standard deviation, along with the infection ratio (ROI) obtained from both the gray-level combination matrix (GLCM) and gray-level running length matrix (GLRLM). These characteristics capture important information contained in the scanned images, enabling accurate and comprehensive classification of different COVID-19 phases.
4) Performance Comparison: We carefully compare the performances of our suggested model to state-of-the-art research approaches in order to demonstrate its superiority. Our systematic testing and comprehensive analysis highlight the superiority of our method, demonstrating its ability to accurately classify and diagnose COVID-19 patients using data from CT scans.

Our study work is divided into several sections in an organized manner. In Section 2, a thorough assessment of the literature is conducted, covering research that are relevant to the diagnosis of COVID-19 and the usage of machine learning methods. In-depth explanations of feature extraction, data preparation techniques, and the incorporation of four different machine learning models are provided in Section 3 of our suggested methodology. We carefully detail the results of our tests in Section 4, doing a thorough analysis and discussion of our findings. In Section 5, they accomplish our work by highlighting the contributions of our study and outlining potential future directions for the development of CT scan-based COVID-19 diagnosis.

## II. LITERATURE REVIEW:

The COVID-19 pandemic has involved significant studies of its potential risk to human life. Intelligence systems have proven valuable in classifying CT images to identify signs of infection and categorize the harshness of COVID-19 cases.

In a recent study by [20], a brand-new two-stage diagnostic method was presented to determine the mark of COVID-19 in CT scans. Research employed transfer learning with the ResNet-50 model, dividing the procedure into two phases. The model first identified photos as either COVID-19 or non-COVID-19. Then, in a second classification phase, it further classified COVID-19 images into categories based on their severity: medium, low, or high. The findings were impressive, showing 97.3% accuracy rates in severity detection and 98.5% accuracy rates in COVID-19 diagnosis, proving the stability and effectiveness of the suggested methodology.

To determine the severity of disease as shown in CT images, [21] used Random Forest (RF) machine learning approaches. Ground-glass opacity (GGO) and the ratio of infected volume to lung volume were two of the quantitative indicators they calculated as part of their technique. These measures demonstrated the versatility of machine learning in extracting information from CT images for COVID-19 assessment, and they were crucial in establishing the extent of the disease. The most important indication of severity among these variables was found to be the ratio of GGO to total lung volume. The predicted COVID-19 severity was predicted with an excellent 87.5 percent accuracy using the provided method. [22] proposed the use of multiple classifiers to distinguish severe from non-severe CT images of COVID-19. They employed various deep learning methods such as Inception-V3, ResNet-101, ResNet-50, and DenseNet-201 to extract image features. Multiple classifiers, including cubic K-nearest neighbors (KNN), SVM, linear SVM, AdaBoost Decision Tree, and linear discriminant, were employed for classification. The DenseNet-201 model with cubic SVM achieved accuracy rates of 95.34% in leave-one-out validation and 95.2% in 10-fold cross-validation.

Convolutional neural networks (CNN) were used by Irmak [23] to develop a fully automated severity classification method for COVID-19 X-ray pictures. Severe, mild, moderate, and critical were the four categories used to classify the severity. Based on lung envelopment and opacities, the author used the COVID-19 lung severity evaluation approach. Grid search optimization was applied to improve the hyper-parameters of the CNN model, yielding an accuracy of 95.52 percent.

To predict the severity of disease, [24] used a variety of deep networks, including VGGNet, AlexNet, ResNet34, and DenseNet. Severe, moderate, mild, and critical were used to describe the severity classifications. While mild, moderate, and severe phases were included in the non-severe stage, severe and critical stages were included in the severe stage. With 81.9% for testing and 97.4% for training, ResNet34 had the best accuracy among the analyzed networks. [25] presented a thorough categorization of COVID-19 severity across four different levels moderate, mild, normal, and severe using information from CT scans. They analyzed a wide range of 28 statistical texture features, including metrics like kurtosis, variance, and skewness, in addition to GLCM, GLRLM, and GLSZM features. They used classic machine learning algorithms like Random Forest (RF), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN) to classify the severity levels. Notably, RF had the highest accuracy rate of 90.95%, demonstrating its superiority among the approaches they examined for severity classification.

[26] used a deep convolutional neural network (DCNN) to classify COVID-19 severity into four levels: severe, moderate, mild, and critical. They trained CNN models based on chest X-ray images dataset and showed the prototype was able to correctly classify these images into the appropriate severity levels. The effectiveness of this method was tested by comparing it to other performance evaluation strategies and proving that it could reliably classify COVID-19 severity levels.

| Ref | Used Techniques | Used Algorithms | Advantage | Disadvantage |
|---|---|---|---|---|
| [3] | Statistical Texture Features (e.g., kurtosis, variance, skewness) | Traditional ML: Random Forest (RF), LDA, KNN | Effective categorization of severity (RF achieved 90.95% accuracy) | Multiple statistical features used |
| [4] | Transfer Learning with ResNet-50 | Classification: ResNet-50 Severity Detection: Two-stage method | High accuracy in COVID-19 diagnosis and severity detection (97.3% and 98.5%) | Not specified |
| [13] | Convolutional Neural Networks (CNN) | Classification: CNN with grid search optimization | Automated severity classification for COVID-19 X-ray images (95.52% accuracy) | Not specified |
| [28] | Quantitative characteristics Proportion of infected volume Ground-glass opacity (GGO) | Machine Learning: Random Forest (RF) | Accurate COVID-19 severity evaluation (87.5%) | Not specified |
| [31] | Deep Learning: VGGNet, AlexNet, ResNet34, DenseNet | Severity Classification: Various deep learning networks (e.g., ResNet34) | ResNet34 achieved best accuracy for COVID-19 severity classification (81.9% for testing and 97.4% for training) | Multiple severity levels used |
| [32] | Deep Convolutional Neural Network (DCNN) | Classification: CNN (DCNN) | Evaluation of COVID-19 severity in chest X-rays | Comparison with other performance evaluation methods |
| [34] | Deep Learning: Inception-V3, ResNet-50, DenseNet-201, ResNet-101 | Feature Extraction: Inception-V3, ResNet-50, DenseNet-201, ResNet-101 | High accuracy in severe vs. non-severe COVID-19 CT image classification (95.34% in leave-one-out validation and 95.2% in 10-fold cross-validation) | Multiple classifiers used (cubic KNN, SVM, linear SVM, Adaboost Decision Tree, linear discriminant) |

## III. METHODOLOGY

The most important things in every research project are to identify the main issue and provide an explicit answer. In our research, which uses CT imaging and machine learning to diagnose and quantify the severity of COVID-19, we acknowledge the significance of clearly defining the problem and providing a logical solution.

Our main concern is refining the efficiency and accuracy of COVID-19 diagnosis with CT scans, and we are now striving to better articulate this problem. Furthermore, we are committed to provide a clear solution that is based on using machine learning algorithms to examine particular data taken from CT scans in order to accurately determine the severity. Enhancing the problem and solution definitions' precision and clarity is crucial for providing a strong basis for the goals and methods of our investigation.

### *A. PROPOSED SYSTEM*

In this study, we developed a multi-stage approach specifically designed for COVID-19 identification and infection assessment. The diagrammatic depiction of our unique approach, designed to move through several stages of infection and aid in COVID-19 detection, is shown in

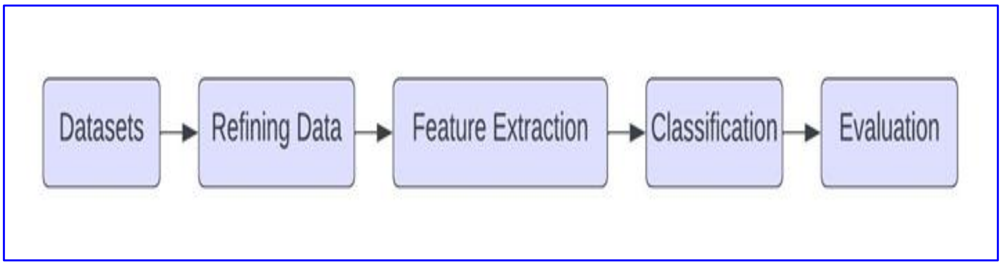



Figure 1. Proposed System

***B. DATASET***

In our proposed system, there are three types of CT scan datasets used [27,28,29]. The collection is composed of two main image classifications: 5001 positive CT images and 9988 negative CT images, which were obtained through comprehensive study throughout relevant fields. Our suggested preprocessing architecture is capable of handling the image duplication in this situation. The dataset specifically consists of 524 non-COVID-19 CT pictures in addition to 409 COVID-19 CT images. In order to maximize our methodology, we take into account using all of the pictures that are accessible, augmenting them with 250 CT scans that are not COVID-19 and 1988 COVID-19 scans to strengthen our dataset for improved model training and resilience.

## *C. Image Data Pre-processed Unit*

In our approach, we process our datasets in two ways: one is removing unit and another cropping unit. We have taken a chest image as a dataset, and 20-30 slices are generated in any CT image chest data from top to bottom. We removed containing slices of image data from top to bottom and kept the slices of the rest of the image data that contain long parts in the removing unit. Inside the cropping unit, we have cropped only the lung parts and removed all the surrounding areas of the image data. These steps are the hardest because all images have different positions of contain lungs. Therefore, we have to do the number of times performed cropping steps for best outcomes. Fig. 2 represents a sample from internal removing and cropping units processed.

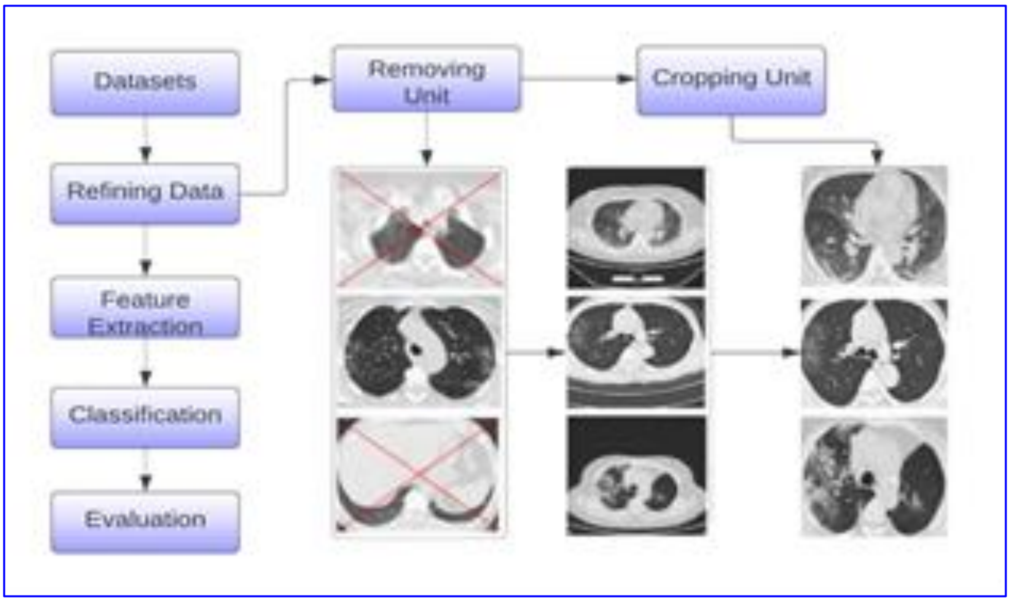



Figure 2. Architecture of removing and cropping images due to pre-processing

## *D. FEATURE EXTRACTION*

In this step of our work, we are considering 16 features to identify infection stages. These features are a ratio of infection stage in Fig. 3, which represents our proposed system to extract [30]. In the masking lung from image data, we improve the strength value of images by method. Then, we create a binary image by technique that converts every value's upper bound of global threshold 1's and rest with 0's. Next, masking the lungs using disk structuring. We have done the mask. Then, we fill the region. After that, they masked the lungs and evaluated the white area in the image [31,32].

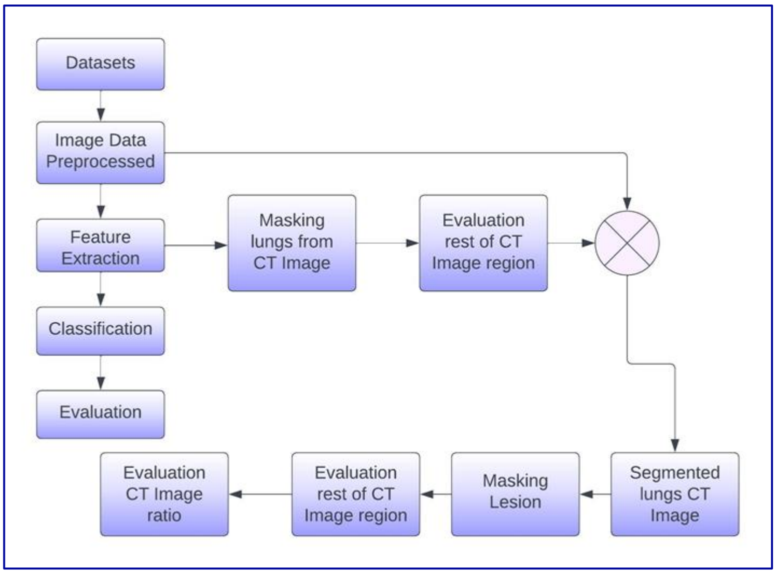



Figure 3. Feature extracting ratio of infection

First, we have taken feedback from segmented lung steps by multiplying the actual and masked images. Lesions that are larger than the threshold value are segmented. Experiments are used to determine these values.

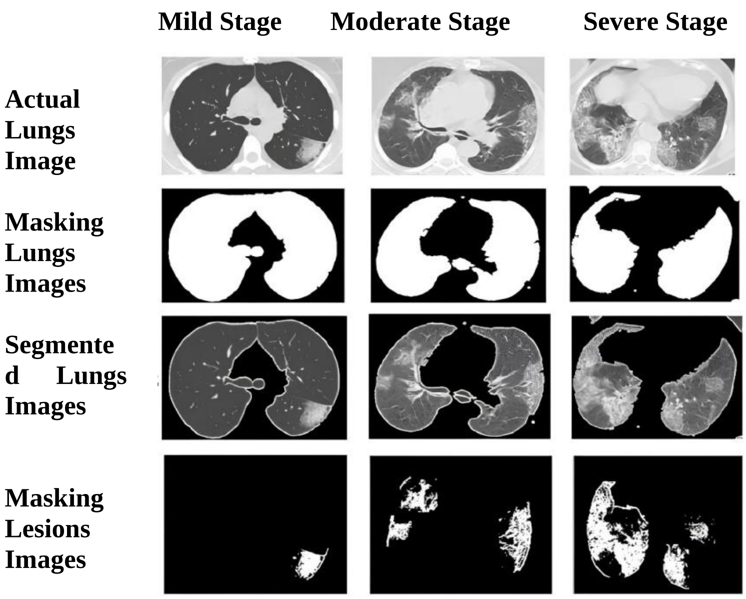



Figure 4. Samples three feature extracting stages

After segmenting the lesions, they identified the white lesions in the inputs. Using the formulae below, we were able to calculate the Ratio of Infection in Fig. 4.

$$Ratio\ of\ infection = \frac{Lessions\ Area}{Lung Area} \tag{1}$$

For statistical texture features, we consider four features standard deviation skewness, mean, and kurtosis which is determined by equation (2, 3, 4, 5):

$$\bar{x} = \frac{\sum_{a=1}^{M} xa}{M} \tag{2}$$

$$s = \sqrt{\frac{\sum_{a=1}^{M} (xa - \bar{x})^2}{M-1}} \tag{3}$$

$$K = \frac{\sum_{a=1}^{M}(xa - \bar{x})^4}{(M-1)\times s^4} - 3 \quad 4$$

$$S = \frac{\sum_{a=1}^{M}(xa - \bar{x})^3}{(M-1)\times s^3} \quad 5$$

where M stands for number of features, x, s is mean, standard deviation respectively

1) ***Unveiling the Potential of Textural Features: A Deep Dive into Grey Level Co-occurrence Matrix (GLCM) and Grey Level Run Length Matrix (GLRLM)***

a) The process of extracting texture features like GLRLM and GLCM necessitates the extraction of information based on histograms from every picture. Important characteristics such as contrast, correlation, energy, and homogeneity are carefully calculated in the GLCM study. Short-run emphasis (SRE), run length non-uniformity (RLN), run percentage (RP), long-run emphasis (LRE), and high gray-level run emphasis (HGRE) are the seven crucial factors identified by GLRLM research. Interestingly, all features in GLRLM and GLCM are obtained in four different angles (0, 45, 90, and 135 degrees) prior to calculating the average, which enhances the overall evaluation of texture properties in images.

1. GLCM stands for Grey level co-occurrence matrix calculations are made for the GLCM's homogeneity, energy, correlation, and contrast [3]. We may compute them using the formulae mentioned in equation (6,7,8,9):

$$contrast = \sum_{i}^{M}\sum_{j}^{N}(i-j)^2 p[i,j] \quad 6$$

$$correlation = \frac{\sum_{i}^{M}\sum_{j}^{N}(i-u)(j-u)p[i,j]}{\sigma^2} \quad 7$$

$$Energy = \sum_{i}^{M}\sum_{j}^{N}(p[i,j])^2 \quad 8$$

$$Homogeneity = \sum_{i}^{M}\sum_{j}^{N}\frac{p[i,j]}{1+|i-j|} \quad 9$$

The variables r and l represent the variance and mean of a picture with dimensions M and N, indicated by i = 1, 2, 3,..., M and j = 1, 2, 3,..., N, respectively.

2. The seven GLRLM features that were recovered are SRE, RP, GLN, LGRE, LRE, RLN, and HGRE [33]. GLRLM stands for grey level run length matrix. On these, we may do the following computations as shown in equation (10, 11, 12, 13, 14, 15, 16):

$$RP = \frac{\sum_{i\in Ng}\sum_{j\in Nr}(pij)}{N} \quad 10$$

$$GLN = \frac{\sum_{i\in Ng}\left[\sum_{j\in Nr}(pij)\right]^2}{\sum_{i\in Ng}\left[\sum_{j\in Nr}(pij)\right]} \quad 11$$

$$RLN = \frac{\sum_{i \in Nr} \left[ \sum_{j \in Ng} (pij) \right]^2}{\sum_{i \in Ng} \left[ \sum_{j \in Nr} (pij) \right]} \quad 12$$

$$SRE = \sum_{i \in Ng} \sum_{j \in Nr} (pij) \quad 13$$

$$LRE = \frac{\sum_{i \in Ng} \left[ \sum_{j \in Nr} j^2 (pij) \right]}{\sum_{i \in Ng} \left[ \sum_{j \in Nr} (pij) \right]} \quad 14$$

$$LGRE = \frac{\sum_{i \in Ng} \left[ \sum_{j \in Nr} (pij / i)^2 \right]}{\sum_{i \in Ng} \left[ \sum_{j \in Nr} (pij) \right]} \quad 15$$

$$HGRE = \frac{\sum_{i \in Ng} \left[ \sum_{j \in Nr} (i^2 pij) \right]}{\sum_{i \in Ng} \left[ \sum_{j \in Nr} (pij) \right]} \quad 16$$

The link between N, the overall number of pixels in the image, Nr, which denotes the range of various run lengths, and Ng, which denotes the range of different grey levels, is shown in the equation 17:

$$N = \sum_{i \in Ng} \sum_{j \in Nr} j (pij) \quad 17$$

A novel approach that is changing the medical field uses CT images to diagnosed novel COVID-19 and determine their severities. Using sophisticated feature extraction techniques, this state-of-the-art method reveals 16 unique features from CT scans. These comprise statistical textural characteristics in addition to characteristics drawn from the GLRLM and GLCM, providing unmatched information about COVID-19 expressions in lung tissue. Specifically, the novel approach comprises complex pre-processing phases with customized removal along with cropping units precisely matched to the lung regions of interest.

Improvements in assessment techniques represent a critical step forward. These more sophisticated methods include thorough assessments that incorporate confusion matrices, ROC analysis, and a variety of performance measurements. This coordinated work makes a substantial contribution to the improvement and validation of machine learning-based methods for assessing severity and diagnosing conditions in clinical settings. Through the coordination of a comprehensive analysis using CT scans, these assessments aid in the development and verification of these techniques. Ultimately, a significant advancement in the accuracy, effectiveness, and dependability of medical imaging-based diagnoses, especially for infectious diseases like COVID-19, has been made with the customized integration and adaptation of various methods and approaches for COVID-19 diagnosis and evaluation of severity using CT scans.

## ***E.****CLASSIFICATION*

We separated the datasets into training and testing stages using the eight-fold cross-validation technique. The images are divided into four stages using four machine learning (ML) techniques, including the severe stage, normal, moderate, and mild in Fig. 5.

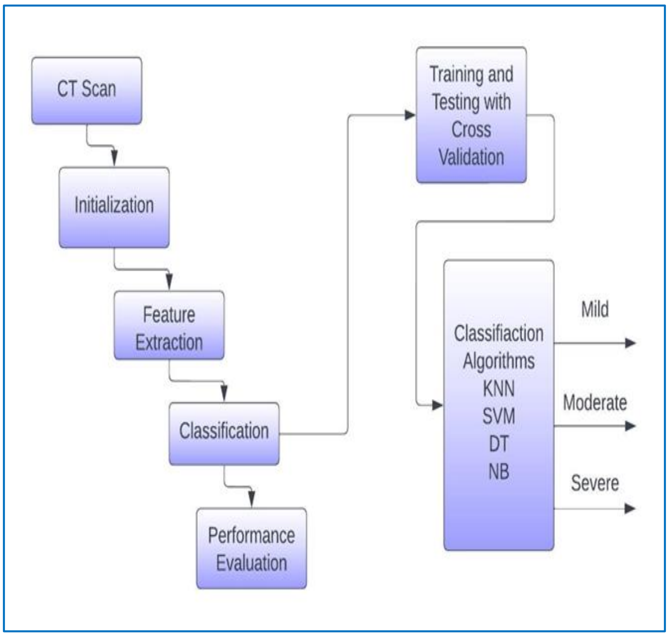
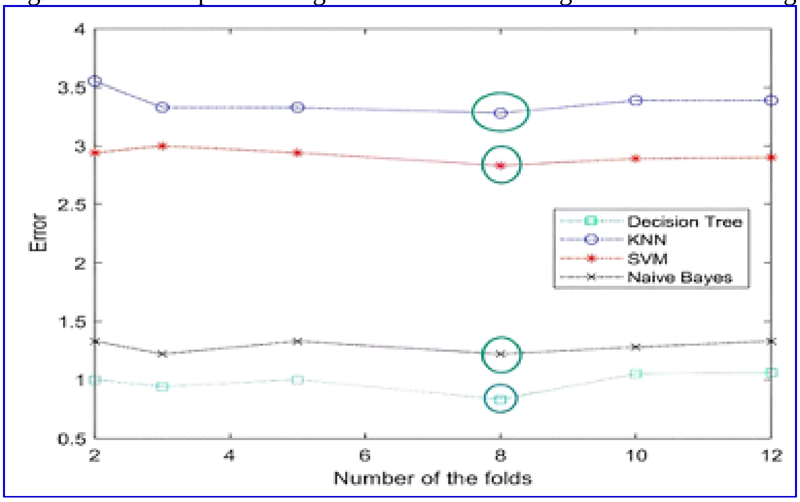



Fig.6 Shown best possible digits of folds for used algorithms for mild stage

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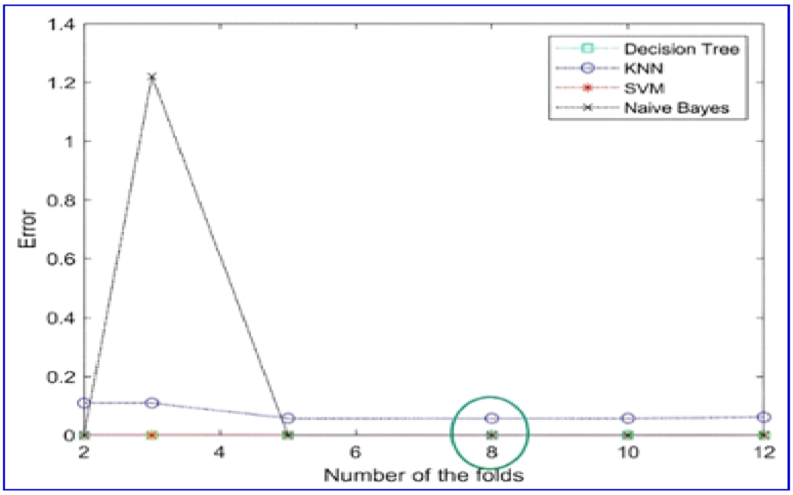



Fig.8 Shown best possible digits of folds for used algorithms for severe stage

### *K-FOLD METHOD FOR CROSS-VALIDATION*

This method is a reliable way to evaluate machine learning models, especially when working with small datasets. It divides the dataset into k sections at random in order to function. Iterations involve allocating k-1 folds for train and test model from the remaining subclasses. As [34] points out, these procedures repetition are k times to ensure comprehensive training and testing throughout the whole dataset.

Following extensive testing, we determined that eight was the ideal K-fold value for our inquiry. This resulted from a painstaking process of trial and error with different fold values. We were able to identify the fold value which consistently produced the lowest mistake rate for each severity level, as clearly illustrated in Figures 6, 7, and 8, by methodically experimenting with various fold configurations. The fold-value dependencies and accompanying error rates for the severe, moderate, and mild COVID-19 levels are clearly shown by these graphic representations.

### *DECISION TREE*

An SML technique may be used for both algorithms; one is classification, and the other is regression for decision trees. The leaf node and the decision node are the two nodes that make up any decision tree. Decision nodes have several branches. The leaf nodes represent the conclusions drawn to support a claim. A decision tree algorithm that starts with a root node can have several branches thanks to this characteristic. It poses a question and only recognizes a yes-or-no response [35].

### *SUPPORT VECTOR MACHINE*

The SVM is the procedure for resolving classifications or regression issues using supervised machine learning (SML). SVM is formally defined as a discriminative classifier that uses separating hyperplanes. Upon receiving labeled training data, the algorithm constructs a perfect hyperplane that groups new classes. In 2D, consider a hyperplane as a splitter that splits a plane toward two distinct parts, dividing each into its own side. This optimal line is computed using the points from two classes with the most significant margin and the closest distance to the hyperplane. Support vectors are locations like this [35-36].

### *NAIVE BAYES*

Classification issues may be solved using the naive Bayes method of SML. It is presumed that each characteristic in a class exists independently of the others. Estimating the probability of the test case allocated to every possible class label works based on the probability principle. The probability with the most significant value determines the label for the test scenario [36,37].

### *K-NEAREST NEIGBHORS*

K-Nearest Neighbors (KNN), an SL method, may be applicable for both regression and classification. KNN selects which K locations are most similar to the test data to attempt to forecast the correct class for the test dataset by resolving the distance amongst it along with all labeled training instances [37,38].

## **F.** *Models (For fine-tuning)*

Through experimentation, we change each classifier's parameters. We select the alternatives that produce the most significant outcomes. We examine three decision tree types: coarse, fine, and medium, which vary in the quantity of splitting. For fine DT, medium DT, and coarse DT, use 100 splits, 20 splits, and 4 divides, respectively. According to the experimental results, Fine DT performs the best out of all the models evaluated. In particular, we examined the effectiveness of the Euclidean, Minkowski, and cosine measures in our examination of distance functions, clarifying their relative efficiency in the attached table. We conclude the Weighted KNN is the most effective algorithm after doing the studies. A description of our KNN experiments may be found in Table 2 below. The weighted KNN is the most effective KNN based on the experiments.

We evaluate the order of three polynomial kernel function levels by Cubic SVM, a kernel scale of one, and the three Gaussian SVM models (Fine, Coarse, and Medium). Each model uses a Gaussian Kernel function, although the kernel scales for each model differ, being 1, 4.1, and 16 accordingly. The experiments lead us to believe this Cubic SVM is the most efficient.

*Table 2. KNN forms associated with their arguments.*

| **Form of KNNs** | **Distance Function** | **K values** |
|---|---|---|
| Fine | Euclidian | 1 |
| Cosin | Cosin | 10 |
| Coarse | Euclidian | 100 |
| Cubic | Minkowski | 10 |
| Fine | Euclidian | 1 |

### *G. Evaluating Performance*

A 33-confusion matrix is depicted in Figure 8, and we investigate various metrics, such as Receiver Operating Characteristic (ROC) area sensitivity, precision, F-score, specificity, and accuracy, to assess the efficacy of the proposed classification methods.

1. True Positive (TP): The prediction was correct, and the label fits the class
2. True Negative (TN): This is a correctly predicted label and does not fall under the category.
3. False Positive (FP): The classifiers continue to produce a positive result even in cases where the label is not exactly aligned with a particular class.
4. False Negative (FN): Despite being a class member, the classifiers predict that the label should be negative.

The evaluation metrics may be calculated using the formulas mentioned in equation (18, 19, 20, 21, 22, 23, 24):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad 18$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \quad 19$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad 20$$

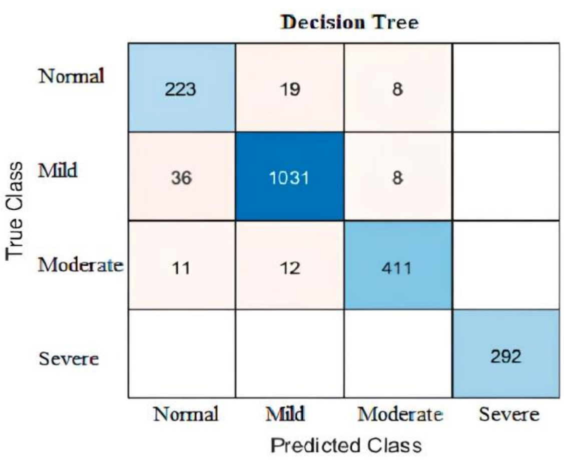
$$Specificity = \frac{TP}{TP+FP} \times 100 \quad 21$$

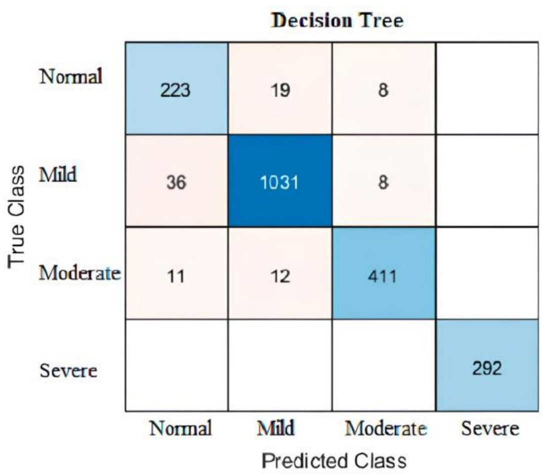
$$F-score = 2 \times \frac{\Pr ecesion \times \operatorname{Re} call}{\Pr ecesion + \operatorname{Re} call} \times 100 \quad 22$$

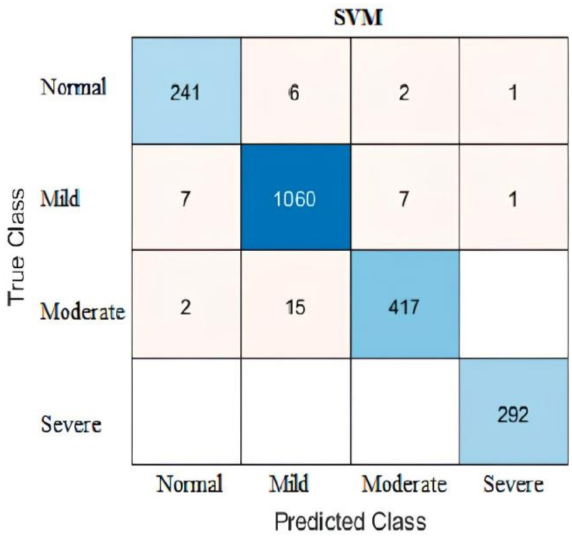
The True Positive (TP) rate is displayed against the False Positive (FP) rate on the ROC graph, which measures the effectiveness of the model. A bigger area under the curve(AUC), which are sophisticated metric for assessing model efficacy, indicates stronger performance when assessing competence.

$$\tau \Pr ate = \frac{TP}{TP+FN} \times 100 \quad 23$$

$$\text{f} \Pr ate = \frac{TP}{TP+FN} \times 100 \quad 24$$





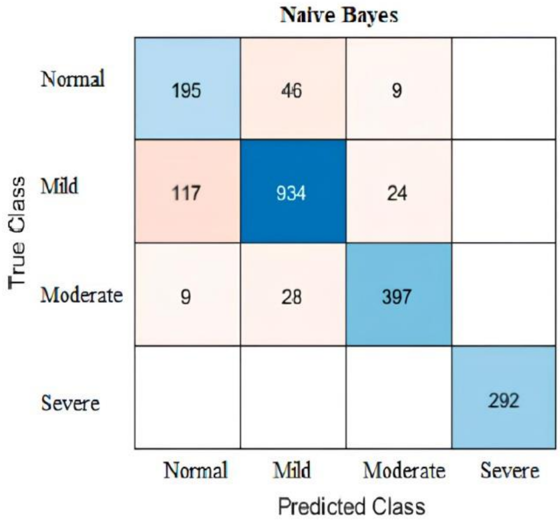




Fig. 9 Shown confusion matrix with proposed approach (a) Decision Tree (b) KNN (c) SVM (d) Naïve Bayes

## IV. EXPERIMENTAL RESULTS AND DISCUSION

On a desktop computer running the Windows 10 operating system, each experiment was developed in MATLAB 2020a. The machine has an Intel 3 GHz Core i5 processor, up to 12 GB of RAM, and an 1115 GB hard drive.

Mild (1075), moderate (434), and severe (292) comprise the four phases of the dataset (2051 scans). These categorizations depend on CT results and the context file supplied through the dataset.

In order to provide a thorough and well-defined approach, our study endeavors were focused on carefully defining and presenting strong methodology for COVID-19 diagnosis along with severity assessment using CT scans. The datasets that were used comprise a wide range of CT scans that have been classified into four categories: severe, normal, moderate, and mild. Clearly, 2051 scans have been identified for study.

We used an eight-fold cross-validation procedure to divide the data into train and test subsets in order to guarantee a thorough evaluation of the model. This approach allowed for a thorough assessment, guaranteeing the accuracy and durability of our model evaluation. We have carefully computed performance measures for every step and model, including F-score, specificity, sensitivity, precision, and accuracy. This allows for a thorough comparison of our suggested method with conventional machine learning algorithms [38-39].

To diagnose COVID-19 severity with machine learning algorithms from CT images, we put transparency first in our process. We provide a thorough overview and go into great detail about our methodology, datasets, assessment measures, and validation procedures. We also describe in detail our feature extraction methods, which include statistical texture features, GLCM, and GLRLM, offering detailed explanations of the particular values that we used in our research. In addition to these explanations, as we have shown in [39], our model comparison table and visual aids, including confusion matrices, ROC curves, and performance tables, provide clarification on our evaluation procedures and results at different phases.

Every scan then goes through our established methodology. We train and evaluate our model using an eight-fold cross-validation process. The parameters for the performance evaluation are briefly shown in Table 4. Additionally, Fig. 9 clearly illustrates the confusion matrices showing the classification results for the classical models SVM, KNN, DT, and Naive Bayes algorithms, emphasizing the accuracy and misclassifications of each model. Fig. 1 displays the SVM model with the fewest missed classification CT scans (41).

Fig.10 represents ROC and AUC curves for every model. The SVM has the greatest AUC (99%) in the graph.

*Result comparison with Proposed Model*

The amount of COVID-19 severity of CT scans based on our research and that of earlier studies is contrasted in Table 4. Consequently, our model performs better than others in terms of accuracy, demonstrating its dependability, effectiveness, and resilience. As stated in [39], this design serves as a dependable and quick tool that enables us to precisely determine the severity of an illness and adjust treatment dosages accordingly.

Clearly, the validity of any research depends on a rigorous validation procedure. In our investigation of novel COVID-19 diagnosis and severities evaluation using CT scans, we have applied eight-fold cross-validation, a widely used technique for model validation. By division of dataset into subsets for train and test model, this method helps to reduce overfitting and increase the model's adaptability, resulting in a reliable and strong evaluation procedure.

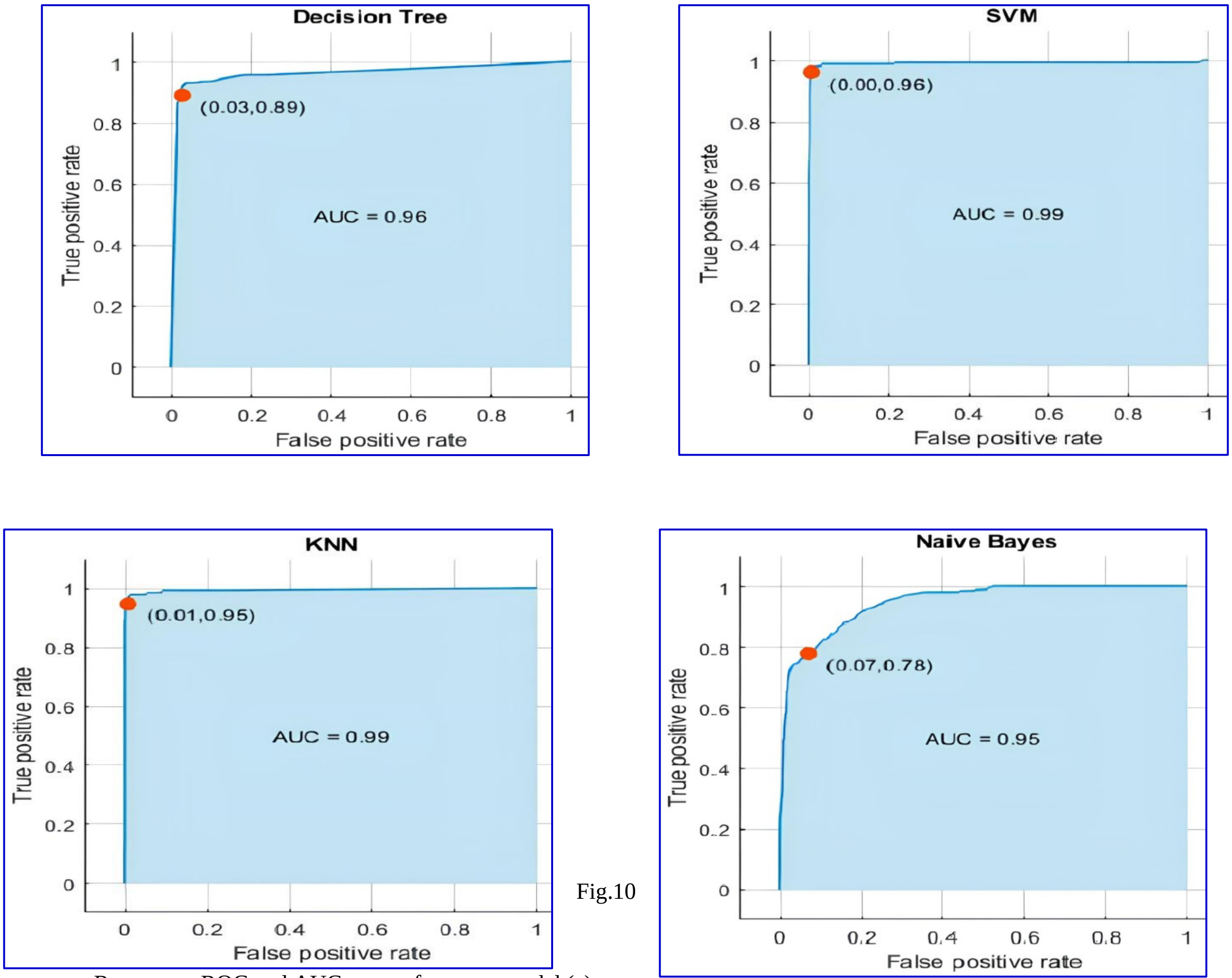



Fig.10 Represents ROC and AUC curves for every model (a) Decision Tree (b) KNN (c) SVM (d) Naïve Bayes

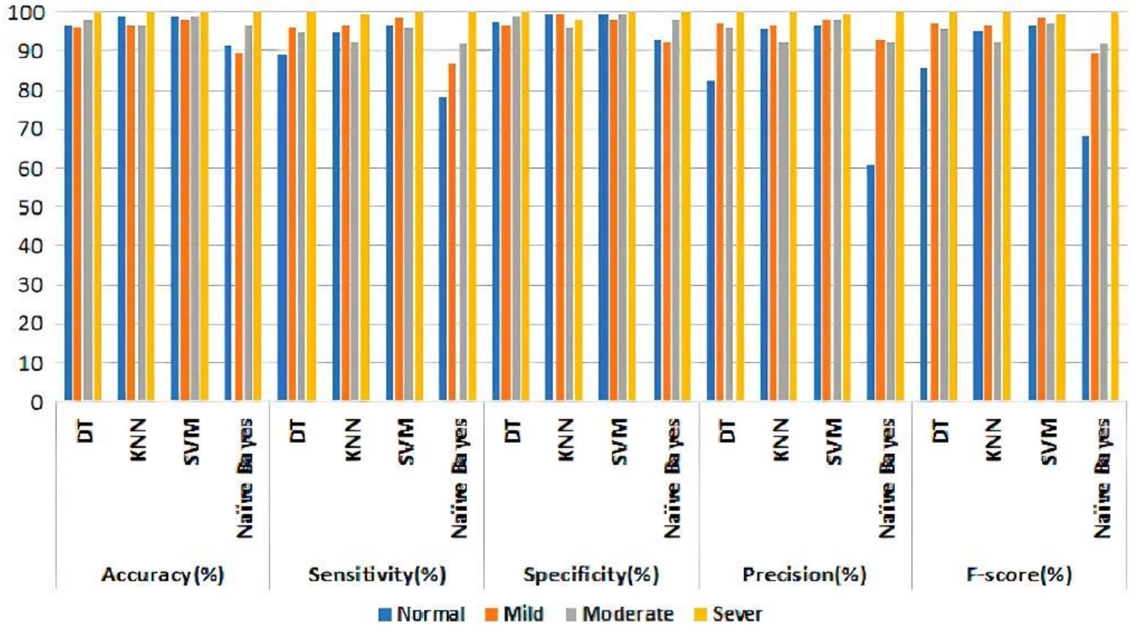



Fig. 11: Performances based on selected stages with proposed model and existing machine learning algorithms

*Table 3.* Performances based on selected stages with proposed model and existing machine learning algorithms as well as considered highest performances of matrices.

| Machine Learning Algorithms | Symptoms Stages | F-Score (High) | Specificity (High) | Sensitivity (High) | Precision (High) | Accuracy (High) |
|---|---|---|---|---|---|---|
| KNN | All | 99.79% (Severe) | 99.77% (Normal) | 99.59% (Severe) | 99.99% (Severe) | 99.89% (Severe) |
| Naïve Bayes | All | 99.99% (Severe) | 99.99% (Severe) | 99.99% (Severe) | 99.99% (Severe) | 99.99% (Severe) |
| Decision Tree | All | 99.99% (Severe) | 99.99% (Severe) | 99.99% (Severe) | 99.99% (Severe) | 99.99% (Severe) |
| SVM | All | 99.71% (Severe) | 99.79% (Severe) | 99.99% (Severe) | 99.79% (Severe) | 99.21% (Normal) |
| KNN | All | 99.79% (Severe) | 99.77% (Normal) | 99.59% (Severe) | 99.99% (Severe) | 99.89% (Severe) |

Table 4. Presentation metrics for our proposed models with traditional models

| Authors | Symptoms Stages | Classification Approaches | Feature Extraction | Performance (%) |
|---|---|---|---|---|
| Tang | Calculating two stages which is Non-Severe and Severe | RF | Lung volume GGO features | 87.50 |
| Irmak | Here four stages are taken which is severe, mild, moderate and critical | CNN | - | 95.61 |

| | | | | |
|---|---|---|---|---|
| Amini and Shalbaf | In this research four stages are taken which is severe, normal, moderate and mild | KNN, LDA, and RF | GLSZM, GLCM and GLRLM | 90.89 |
| Yu | Calculating two stages which is Non-Severe and Severe | LDA, Decision Tree Linear SVM, etc | ResNet-101,V3, DenseNet-201and ResNet-50, | 95.20 |
| Our propose d model | Our four stages are severe, normal, moderate and mild | Naive Bayes, DT, SVM and KNN | ROI, GLCM and GLRLM | 99.00 |

## V. CONCLUSION

This work provides an elaborate architecture that includes lung and lesion segmentation along with COVID-19 identification and severity evaluation using CT scans. By means of a thorough assessment of several division grids, we examined and compared a number of cutting-edge machine learning approaches to determine which ones worked best. The segmentation, classification, and quantification of infection were accomplished with excellent performance levels by the provided models and scheme. These algorithms, Naive Bayes, KNN, DT, and SVM, are used to classify CT images. Studies show that the accuracy of our model ranges from 99.12% for a normal stage to 98.73% for the moderate stage to 98.24% for the mild stage to 99.9% for the severe stage. Additionally, our model performs better than modern ones.

Although our model depends on CT scans, upcoming research will also reflect other factors, including background disease (such as diabetes, etc.), significant blood tests, and demographics that may affect the COVID-19 severity. These characteristics offer insightful information that may increase the precision of our proposed approach. The size of dataset has spends with more data as well as more algorithms for learning are used.

**List of Abbreviations**

*Table 5: List of Abbreviations*

| S.no. | Abbreviations | Full form |
|---|---|---|
| 1 | CT | Computed Tomography |
| 2 | DT | Decision Tree |
| 3 | GGO | Ground-Glass Opacity |
| 4 | GLCM | Gray-Level Co-Occurrence Matrix |
| 5 | GLRLM | Gray-Level Run-Length Matrix |
| 6 | GLSZM | Gray Level Size Zone Matrix |
| 7 | HGRE | High Gray-Level Run Emphasis |
| 8 | KNN | K-Nearest Neighbors |
| 9 | LGRE | Legal & General's Specialist Life Reinsurer |
| 10 | LRE | Long-Run Emphasis |
| 11 | LRE | Linezolid-Resistant Enterococcus |
| 12 | MERS | Middle East Respiratory Disease |
| 13 | RL | Reinforcement Learning |
| 14 | RLN | Run Length Non-Uniformity |
| 15 | ROI | Ratio Of Infection |
| 16 | RP | Run Percentage |
| 17 | RT-PCR | Reverse Transcription Polymerase Chain Reaction |
| 18 | SARS | Severe Acute Respiratory Syndrome |
| 19 | SL | Supervised Learning |
| 20 | SRE | Short-Run Emphasis |
| 21 | SVM | Support Vector Machines |
| 22 | USL | Unsupervised Learning |

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