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A Comparative Study of HARR Feature Extraction and Machine Learning Algorithms for Covid-19 X-Ray Image Classification

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Abstract— In this study, we investigated how effectively COVID-19 image categorization using Harr feature extraction and machine learning algorithms. We were particularly interested in the effectiveness of these algorithms. A dataset of 500 X-ray scans, equally split between 250 COVID-19-positive cases and 250 healthy controls, served as the basis for our study. K-nearest neighbors,decision tree, Linear regression, support vector machine, regression, classification, naive Bayes,random forest, as well as linear discriminant analysis were among the seven machine-learning approaches used to categorize the photos. With the use of Harr feature extraction, the features of the pictures were extracted. We studied the efficacy of COVID-19 X-ray images for classification utilizing the combination of machine learning as well as the Harr feature extraction methods in the present investigation due to their effectiveness. We searched a database of 500 X-rays for this investigation, dividing them equally between groups of 250 patients with COVID-19-positive cases and 250 healthy people. Following that, the images were examined using seven various machine learning approaches for recognition. These methods included naive Bayes, linear discriminant analysis, random forests, classification,k-nearest neighbors, and regression trees. The information from the photos was gathered using the Harr feature extraction method. The effectiveness of the algorithms was evaluated with the help of a variety of metrics, such asF1 score, precision,accuracy, recall, the area under the ROC curve, and the region of interest curve. According to our research, the Support Vector Machine algorithm had the highest accuracy, at 77%, while the Naive Bayes approach had the lowest accuracy, at 58%. By using machine learning and Harr feature extraction approaches, the Random Forest method yields the best results, based on our research. The development of future COVID-19 X-ray image-based automated diagnostic systems may be influenced by these findings. Results from the suggested model were comparable to those of cutting-edge models trained using transfer learning techniques. The proposed model's main advantage is that it has ten times fewer parameters than the most advanced models.A receiver operating characteristic (ROC) curve's F1 score, and the algorithms' accuracy, precision, the area under the curve, and recall were all used as metrics. According to our findings, the Naive Bayes method gained the least accuracy (58%) and the Support Vector Machine method produced the highest accuracy (77%) when used. Our results reveal that employing Harr feature extraction and machine learning techniques, the Random Forest strategy is the most successful way to recognize COVID-19 X-ray pictures. These findings may be pertinent to the development of automated COVID-19 diagnosis tools relying on X-ray images. The recommended model produced results that were competitive when measured against cutting-edge models trained using transfer learning techniques. The suggested model employs 10 times fewer parameters than the most advanced models, which is its key selling point.

Keywords- Support Vector Machine, Linear Discriminant Analysis, Covid-19, Xray, K- Nearest Neighbor, Native Bayes, Random Forest.

I. INTRODUCTION

Billions of human beings throughout the world have fallen victim to the extremely infectious COVID-19 virus. Early diagnosis of the disease is crucial for effective treatment and for reducing the spread of the virus [1]. X-ray imaging displays the primary methods used to diagnose COVID-19, and it is highly effective in identifying the disease in patients.However, X-ray images can be complex, and the interpretation of these images can be challenging, especially in cases where the disease is in its early stages [2]. In this section, Harr feature extraction methods and machine learning algorithms (MLA) are very helpful. COVID-19 X-ray pictures can be more accurately and efficiently classified with the use of these techniques, thereby enabling healthcare professionals to make informed decisions about treatment and care [3].

Researchers have started using computer-aided identification (CAD) more frequently recently to identify and segment diseases in medical images [4]. As soon as it was possible to scan in and save medical images digitally, the practice of automatically analyzing them began. When it comes to interpreting medical images, rule-based methods have given way to supervised procedures in recent years. Our data-driven model for image analysis was built using statistical classifiers, atlas methods, and dynamic shape models [5]. Only data carefully collected and selected by humans can be utilized to train these algorithms. If you wish to execute this difficult work successfully, you must have a lot of experience with medical imaging. Over the last decade [6, 7], automated feature extraction has become widely used, thereby eliminating the requirement for professional feature engineering. At the moment, the convolutional neural network (CNN) is an effective deep learning technology for imageprocessing.To automatically extract and identify high-level information from the images that it is fed, CNN uses a variety of layers of convolutional methods [7].

Early testing enables the detection of COVID-19 virus carriers who are asymptomatic. Additionally, precise categorization of the X-ray image can help in differentiating COVID-19 from other respiratory disorders like pneumonia, which lowers the risk of receiving an inaccurate diagnosis and increases the likelihood that the patient will receive prompt treatment [8]. Both conventional machine learning methods and deep learning strategies can be employed for categorizingX-ray COVID-19 image data [9]. The classification of data is the next step in standard machine learning systems [10], and for this, algorithms like decision trees, logistic regression, and support vector machines are adopted. Also, deep learning algorithms employ CNNs to automatically extract important information from photos. Both traditional and deep learning systems have severe limitations when trying to categorizeX-ray images of COVID-19 [11]. As a result, more research is required to develop better and more effective techniques for COVID-19 diagnosis[12]. Finally, the detection and diagnosis of illnesses, the decrease in false diagnoses, and the outcomes for patients can all be significantly improved by the classification of COVID-19 X-ray pictures using MLA and Harr feature extraction approaches.

II. METHODOLOGY

Patients' X-ray scans are gathered for this investigation, some of whom have COVID-19 and others do not. Following the extraction of the Harr characteristics from the images, MLA would be used to categorize the pictures as COVID-19 or non-COVID-19. Finally, evaluate each model's performance. The block diagram in Figure 1 shows the following. A new dataset has been created by combining the "COVID-19 Image Data Collection" and the "RSNA Pneumonia Detection Challenge dataset" [2, 3]. To address a categorization issue, the recently created dataset known as COVIDx considers three classifications: pneumonia, Normal, as well as COVID-19. The dataset is categorized into two parts: a training as well asa testing (also known as model assessment) partition. Overall images within the dataset are 13,800, which were shot by 13,645 different people. The dataset's source code can be accessed by anyone interested by visiting https://github.com/lindawangg/COVID-Net. The dimensions of an image might range from 156 by 157 to 4032 by 3024 pixels.

To lessen the amount of noise and enhance the overall image quality, the dataset is preprocessed. After preprocessing, pictures are subjected to the Harr feature extraction procedure to isolate crucial traits that can support classification. To improve classification accuracy and make computations simpler, one might use a feature selection technique to select the features that are most relevant to the current issue. Efficacy is evaluated using a range of criteria when comparing the effectiveness of different machine-learning algorithms. These measurements include things like precision, accuracy, F1 score,recall, region of interest curve (ROC), as well asthe area under the ROC curve (AUC).

A. *Data Preprocessing and Augmentation:*

Cleaning, noise reduction, and outlier elimination are just some of the pre-processing tasks that may be accomplished with the help of various methods. The pixels in the image are examined here with their intensities normalized to the interval [0,1]. Use the filter to smooth out the image as well. If the semantic information is preserved, data augmentation involves modifying images within the dataset to add to the training set. In our work, for instance, we modified the radiographs by rotating them, flipping them horizontally, and enlarging them. Images are flipped horizontally (with a 50% chance), magnified (by up to 20%), and rotated by up to 15 degrees (in either direction). A probability may permit the use of all, some, or none of the modifications.

B. *Haar feature extraction:*

Haar feature extraction is a technique used in computer vision to detect patterns in images. It involves the use of Haar wavelets, which are mathematical functions that can be used to decompose an image into its constituent parts. These parts can then be used to identify patterns and features in the image. To apply Haar feature extraction to COVID X-ray images, you would first need to train a classifier to recognize COVID X-rays.

C. *Classification Algorithms:*

Algorithms including LR, RF, NB, SVM, CART, KNN, and LDAfor classification.

1) Linear regression:

Classifying COVID-19 X-Ray images is not a job for the linear regression machine learning technique. Predicting categorized labels like "COVID-19 positive" / "COVID-19 negative" is an example of classification, while the linear regression model predicts continual numerical values. The linear regression is represented as follows;

$$\mathbf{y = b0 + b1*x} \qquad (1)$$

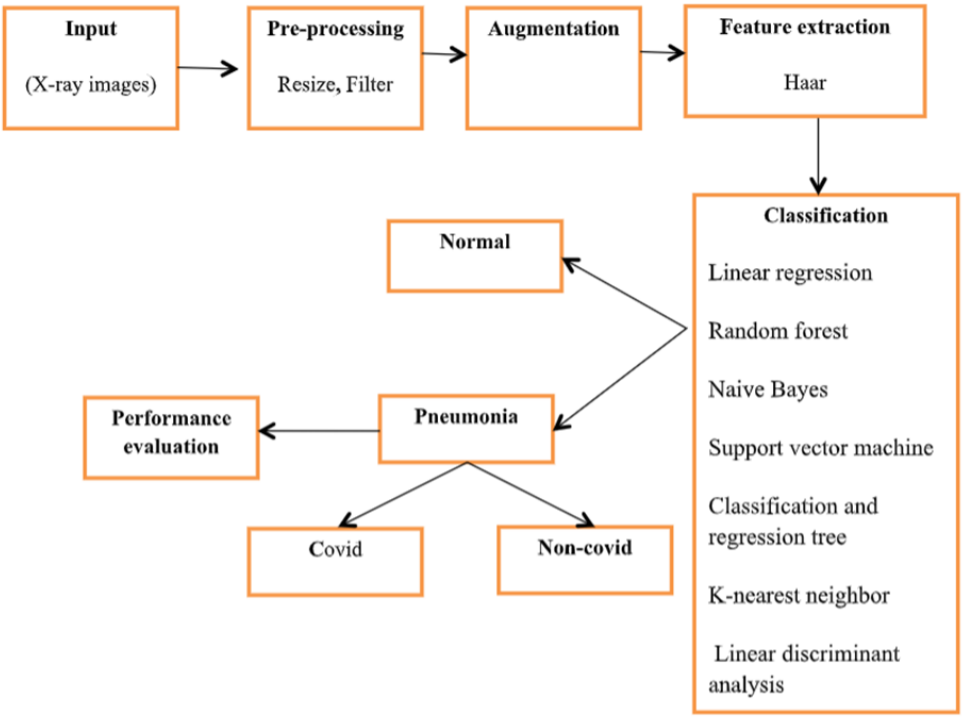

Fig: 1Proposed Block Diagram

In this equation, x denotes the COVID-19 classification label as the independent variable, y denotes the Haar features that were recovered from the X-Ray image as the dependent variable, b0 denotes the intercept, and b1 denotes the coefficient that characterizes the relationship between x and y.

2) Linear Discriminant Analysis:

LDA refers to a generalized method for machine LDA refers to a generalized method for machine-learning classification problems. It shines in situations where there are several classes as well as maximizing the gap between them requires finding a straight-line arrangement of attributes. LDA may constitute used to discover a linear discriminant that divides COVID-19 X-Ray pictures into two distinct categories, one positive and one negative.

The mathematical equation for LDA is as follows:

Calculate the mean vectors for the two classes:

$$\mu 1 = (x11, x12, ..., x1n)\ \mu 2 = (x21, x22, ..., x2n) \quad (2)$$

where n features counts and x_{ij} is the jth feature of the ith sample. Calculate the within-class scatter matrix:

$$Sw = S1 + S2 \quad (3)$$

where S1 and S2 are the scatter matrices for each class:

$$S1 = \Sigma(xi - \mu 1)(xi - \mu 1)T\ S2 = \Sigma(xi - \mu 2)(xi - \mu 2)T \quad (4)$$

Calculate the between-class scatter matrix:

$$Sb = (\mu 1 - \mu 2)(\mu 1 - \mu 2)T \quad (5)$$

Find the linear discriminant that maximizes the separation between the classes:

$$w = S\text{^-}1b\ (\mu 1 - \mu 2) \quad (6)$$

Project the data onto the linear discriminant:

$$y = wTx \quad (7)$$

where y is the new feature and x is the original feature vector.

To determine if a picture is COVID-19 either positive or negative, a threshold value is applied to the y-coordinate. Keep in mind that LDA presumes a distribution that is normal for the information and that its matrix of covariance is the same for all categories. If these conditions are not satisfied, different classification methods may be better suited for X-Ray imaging ofCOVID-19.

3) Support Vector Machine:

To analyze COVID-19 in photographs of X-rays, you can use SVM, a well-liked machine learning technique to classify jobs. The identification of objects in images is possible with Haar features, while SVM may be employed in COVID-19 detection using X-ray imaging. This helps for COVID-19 identification using support vector machines with Haar characteristics is feasible, but it requires careful

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dataset curation, feature selection, and model tuning to achieve accurate and reliable results. Further research and validation are needed to establish the performance and clinical applicability of this approach in real-world healthcare settings.

4) Classification and Regression Trees:

Decision trees are important to the CART (Classification and Regression Tree) machine learning technique. From there, a binary tree will be constructed, with each leaf node representing a different class name, every node within the network is meant to represent an attribute assessments, as well as each branch is meant to reflect the outcome of the test. The COVID-19 X-ray image classification training process requires the extraction of a set of features from the images, such as Harr features, and the application of COVID-19 positive or negative class labels. Adding positive or negative class labels to the photos is another stage. With each iteration, the algorithm creates subsets of the data that are as monolithic (i.e., representative) as possible of the original data. This is realized because of these characteristics. The process will proceed until one of the criteria for its completion, such as the maximal tree depth or the amount of samples that must be collected from each leaf, is satisfied. A few examples are:

Splitting criterion:

At each internal node of the tree, a splitting criterion is used to determine which attribute to split on and the threshold value for the split. To achieve this goal, the impureness of the ensuing subsets is quantified by a cost function and minimized. One commonly used cost function is the Gini impurity, which is defined as:

$$\mathrm{Gini(p)} = \sum_{i=1}^{c} \mathrm{p_i} \left(1 - \mathrm{p_i}\right) \tag{8}$$

where C class number and p_i is the proportion of samples in class i.

Prediction:

After the tree has been built, a fresh specimen can be categorized by following a path from the beginning through the leaf node and utilizing the criteria for the division at every node to select the direction to take. The projected label for the class is the class to which the leaf node's contents most closely belong.

Pruning:

The CART algorithm could be pruned to prevent overfitting by cutting off any branches that do not lead to better results on a set that has been validated. This is done by calculating the cost-complexity pruning parameter:

$$\alpha = \frac{R(t) - R(T_t)}{|T_t| - 1} \tag{9}$$

where t is a subtree, T is the whole tree, R(t) is the overall misclassification cost of the subtree, and |T_t|is the amount of subtreeleaf nodes. These subtreeshavingthe smallest alpha value are pruned.

5) K-Nearest Neighbors:

Since it does not depend on variables, the method for machine learning known as KNN may constitute utilized for classification as well as regression. KNN is utilized to categorize the COVID-19 X-Ray images. This is accomplished by first locating the k-nearest neighbors within the training set, followed by making utilization of the labels assigned to those neighbors to determine the categorization of the input image. The algorithm uses a distance metric to determine which of the photographs from the training batch most closely resembles the input image. The KNN algorithm is controlled by the hyper-parameter K, which specifies how many neighbors should be taken into account. When K is smaller, the decision boundary is less difficult, but when K is greater, overfitting the data is a possibility. When K is smaller, the decision boundary is more complex, but when K is greater, it is feasible to overfit the data. Through the use of cross-validation, the ideal value of K can be found.

6) Native Bayes:

NB is a probabilistic machine learning method that can be used to discover solutions in situations involving classification. The algorithm for categorizing COVID-19 X-Ray images uses Naive Bayes to calculate the likelihood of each class label (COVID-19 positive or negative) given the input features (the Harr features extracted from the X-Ray images). These qualities are collected out of X-Ray images themselves. The method then returns a class label for the input image that has the highest probability of being correct.

P(class|features) = P(features|class) * P(class) / P(features) (10)

The probability of the class is represented by the symbol P(class), the probability of the input features is represented by the symbol P(features|class), and the probability of the input class is represented by the symbol P(class).

To make the computation of P(features|class), which is a mixture of the individual possibilities of each

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feature assuming the class, as simple as possible, the Naive Bayes approach assumes that the input features are conditionally independent given the class. This is done so that the algorithm may simplify the following things:

P(features|class) = P(feature1|class) * P(feature2|class) * ... * P(featureN|class) (11)

where feature1, feature2, ..., and features are the individual Harr features extracted from the X-Ray image.

7) Random Forest:

RF indicates some machine learning approach that is utilized for segmentation applications, including the categorization of COVID-19 X-ray imaging. The training phase of the method involves the construction of many decision trees, followed by the end of the phase, the algorithm returns the class which is how the classes that were returned by each tree are in turn. In COVID-19 X-ray image categorization it has been demonstrated that RF is superior to Machine Learning Algorithms (MLA) including LR, SVM, and KNN in terms of accuracy and performance. However, it is essential to keep in mind that the effectiveness of the algorithm is contingent on the level of accuracy of the data as well as the hyperparameters that are selected. The efficacy of the model can be optimized by adjusting hyper-parameters.

The training set D is equal to{(x1, y1), (x2, y2), ..., (xn, yn)}, the algorithm creates T decision trees by utilizing a bootstrapped sample of the training set. Each xi in the algorithm represents an input vector with d dimensions, and each yi represents a label. The method picks a randomly selected group of m features at every point in any choice tree, followed by something it selects the feature that maximizes a splitting criterion including information gain as well as the Gini index. This is done so the fact that the algorithm can proceed with making its decisions. This process is repeated until all possible features have been exhausted. The depth of the trees is increased to their greatest potential or until a predetermined stopping condition is reached. The ensemble of T decision trees that are produced as a result of the algorithm is used to generate a forecast by either averaging or voting on the results produced by each of the individual trees.

The objective of the study that contrasts the use of MLA with Harr feature extraction to determine which technique is superior for accurately categorizing X-ray images for COVID-19 detection. The process of identifying particular patterns inside an image by utilizing Haar wavelets is known as Harr feature extraction. On the other hand, MLAs are programmed to learn from the data and to generate predictions based on the patterns that may be found in the data.

III RESULT AND DISCUSSION

The study would compare the accuracy of different MLAs, such as LR, RF, NB, SVM, CART, KNN, and LDA for classifying the X-ray images. The study would also compare the accuracy of using Haar feature extraction versus not using it.The results of this study could have important implications to enhance COVID-19 prediction by X-ray images. By identifying the most accurate classification method, medical professionals could more quickly and accurately identify patients with COVID-19, potentially leading to earlier treatment and better outcomes.

A. Accuracy Evaluation:

To assess their reliability, data-gathering algorithms are trained using assessment methods. The strategies use machine learning (ML) techniques to assess the effectiveness and efficiency of the prototype. Specificity, responsiveness, and precision provide those key performance assessment strategies for the ML model. The proportion of a dataset dictates precision properly categorized cases for the method designed by MLA is

$$Acc = (TP + TN)/ (TP + FP + TN + FN)$$

where TP = True Positive, TN = true -ve, FP = false +ve whilst FN = false negative.Below, we quantify sensitivity as a proportion of predicted nodular variables as well as precision as per percent of predicted intake pictures.

$$Se = TP/(TP + FN) \quad (12)$$

$$Sp = TN/ (TN + FP) \quad (13)$$

The false positive ratio (FPR) refers to the percentage of incorrectly characterized nodule pixels, and the false negative ratio (FNR) appears to be the percentage of incorrectly reported pixel values.

$$FPR = FP/(TP + TN) \quad (14)$$

$$FNR = FN /(TP + TN) \quad (15)$$

The overlapping score indicates how closely the principles' subdivision result corresponds to the real world.

$$Overlap = TP/(TP + FP + FN) \quad (16)$$

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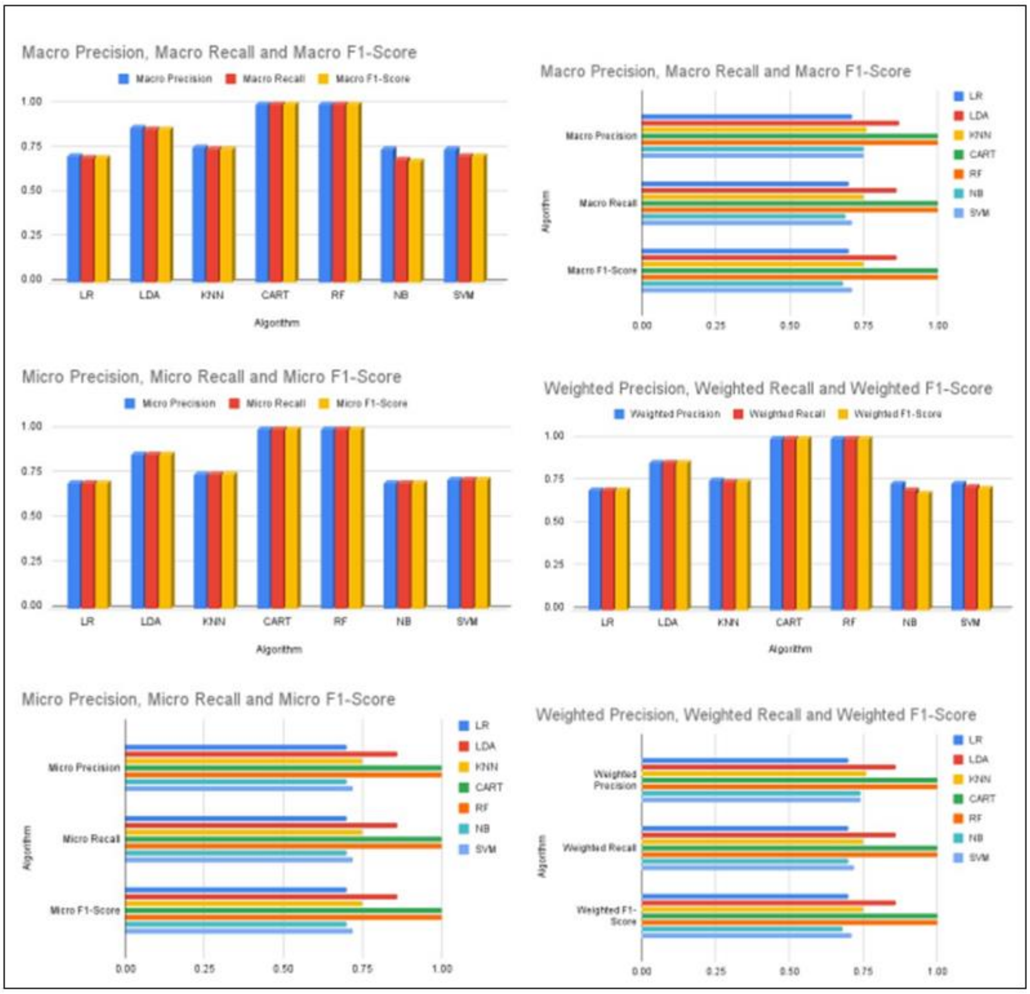
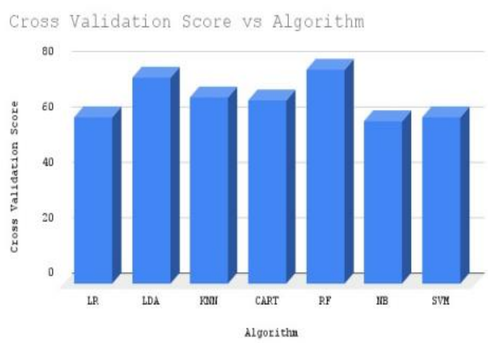


Figure 2. Performance analysis of various algorithms

Where the positive result equals the actual value found as a pixelated nodule. Nodule pixels incorrectly counted as a result of a false positive. The number of background pixels accurately identified = true positive minus negative. The number of photos incorrectly identified as backgrounds = False Negative. Numbers are used in computations, from zero to one. The better the segmentation performance, the lower the FPR and FNR. Figure 2 depicts the measures used to assess performance, such as the area under the curve (AUC), the kappa and Jaccard coefficients, the F-score, the net present value (NPV), the false positive rate (FPR), and the false negative rate (FNR).

B Cross Validation:

To evaluate and check the efficacy of a machine learning model, cross-validation (CV) is employed. CV is a technique employed to prevent a model from being overfitting when there is insufficient data. It is commonly utilized in situations where the goal of the simulation is a prediction as well as goes by the names rotation estimate & out-of-sample testing. That resampling method can additionally be utilized to evaluate the efficacy of various ML models for a given problem-solving task. Put otherwise, CV is a technique for evaluating the efficacy of ML models. In CV, the initial data sample is split up into smaller groups at random. ML is trained on all except one of the datasets. The model is then put to the test by causing predictions on the rest of the subset after the training is complete. Figure 3 depicts the CV using several MLAs for X-ray image classification, including LR, RF, NB, SVM, CART, KNN, and LDA.



C. Confusion Matrix:

In a confusion matrix, every single column and row stands for the actual class and the predicted class, respectively.

Accurately classified data can be seen in the cells that are diagonally aligned. The off-diagonal cells display the misclassified information. Each cell displays the total number of observations as well as a percentage distribution of those observations. The precision of the global estimate is shown in the cell to the right of the plot's foot. The resulting image is shown in Figure 4. To detect covids, the suggested method uses LR and achieves an accuracy of 60.27. Comparison: RF: 77.50, NB: 58.88, SVM: 60.27, CART: 66.25, KNN: 67.36, LDA: 74.44. Figure 5 shows the resulting confusion matrix.

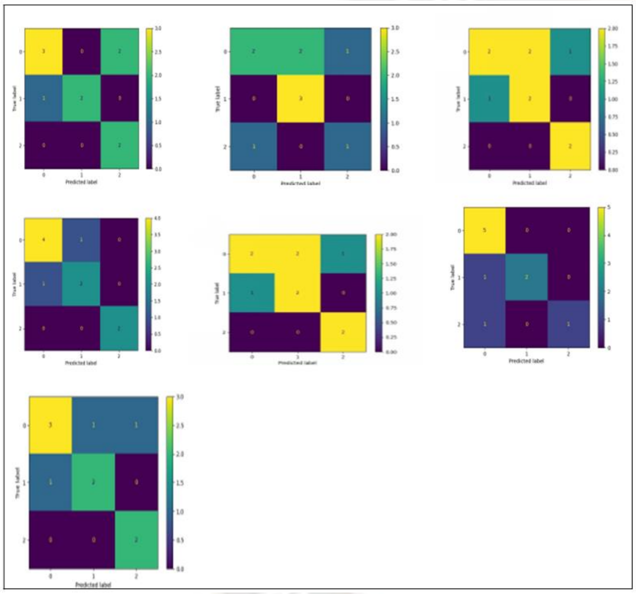


Figure 5. Confusion metrics by the evaluation of algorithms

A similar rise in parameters is generated when the model's depth or width is increased. The hardware requirements are sensitive to the number of parameters defined by the model, energy, and memory needs of the system as well as the training and inference rates. Because there are so many factors, it is necessary to use expensive parallel processing equipment. The best result is typically to enhance the performance of a model with fewer input parameters. Another difficult task is building a deep CNN model for lung segmentation and disease detection in Covid X-Ray images. The clavicle bones and rib cages are visible on the Covid X-Ray. The precise nature of the lesion hiding behind these skeletal fragments may be difficult to ascertain. The likelihood that some of these lesions may be overlooked by the models is increased by this. The models were perfect for lung segmentation tasks since they could easily distinguish between normal and noduled lung tissue in CXR pictures. Lungs damaged by nodules can be used to accurately assess the segmentation of healthy lungs. The evaluation of the incredibly abnormal lungs revealed other significant issues. This is brought on by a nodule, a benign lung abnormality that nearly never affects the structure of the lung. This is particularly true if the nodules in question are small or do not exist in the lungs' outer lobes. The great majority of the various lung shapes, therefore, fall within the usual range. However, other lung conditions like tuberculosis, pneumothorax, and pneumonia can also drastically alter the shape of the lungs. The contour of the lung will change from that of a healthy lung when the lung collapse is severe enough to result in an effusion. The aberrant lung shapes may be difficult for segmentation algorithms to handle, especially those that have only been trained on normal lungs. This makes it essential that data used to evaluate autonomous lung segmentation models contain illustrations of atypical lung forms.

III. CONCLUSION

The comparative study of Haar feature extraction and MLA for COVID-19 X-ray image classification provides valuable insights into the performance of different approaches for COVID-19 detection. Haar feature extraction is a simple and efficient method for capturing local intensity changes in X-ray images withMLAs such as LR, RF, NB, SVM, CART, KNN, and LDA. According to the results of the research, picking the right feature extraction technique is crucialand MLA can significantly impact the efficayofX-ray on COVID-19 classification. The results may vary depending on the dataset used, the size and quality of the images, and the specific implementation of the algorithms.Future research will involve validating the suggested approach while also taking into account a group that has normal as well as abnormal chest X-rays, CT, and ultrasound images. Moreover, research will also be focused on deep learning and formal verification methods and whether theymay achieve superior results in COVID-19.

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