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Deep leraning based Detection Model for coronavirus (COVID-19) using CT and X-ray image Data

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Abstract*—COVID-19 is extremely infectious that spreads quickly from across the world, making early diagnosis critical. COVID-19 diagnosis is critical. Numerous investigations have been performed to ascertain if patients' chest X-rays, as well as computed tomography (CT), scans reveal COVID-19 infection. COVID-19 illness results on computed tomography (CT), as well as X-ray imaging, are like those of other lung infections, making it problematic for medical experts to differentiate COVID-19. The purpose of this research has been to determine the role of machine learning, deep learning, or pictures processing within fast or precise identification of COVID19 from two of the most frequently used medical imaging modalities, chest X-ray or CT pictures. We evaluated performance of ML and DL techniques on chest X-ray pictures as well as CT scans to COVID-19 diagnosis in this research. The proposed convolutional neural networks (CNNs) using the Alexnet Model for CAD of coronavirus from CT and X-ray pictures. The efficiency of this technique was checked on the data set obtained. We classified COVID-19 CT & X-ray scans as well as examined the evolution of the condition of the patients via CT scans. Accuracy of these techniques varied from 93.25 percent to more than 99.82 percent, suggesting that machines, as well as deep learning methods, apply to the clinical diagnosis of COVID-19. The trials carried out in this research have shown the efficacy of the pretrained COVID-19 alexnet model of CNN.

***Keywords*— COVID-19, Machine Learning, Deep Learning, CNN, Alexnet Model.**

I. INTRODUCTION

The Severe Acute Respiratory Syndrome 2 (SARS-CoV-2) virus family causes COVID-19, a contagious disease. It can be passed from person to person and has sparked worldwide concern. The volume of cases streaming into hospitals and health facilities all around the world is overwhelming. Clinicians and scientists all over the world are working on virtual treatments that prevent infected patients from coming into contact with doctors. Images of the lungs, such as CT scans and X-rays, are the most readily available source of data for detection. Using AI technology, the process of taking these photos can be made contactless, removing part of the risk given to health workers. The integration of AI has enhanced the contactless process of gathering picture data for diagnosis, which has increased the purpose of medical imaging. Deep learning, machine learning, face recognition, infrared imaging, GPS, and Bluetooth have all been utilized to detect and diagnose symptoms as well as follow suspected patients while reducing the danger of infection and dissemination. Following the COVID-19 outbreak, many sorts of activities in the areas of epidemic tracking and management were carried out. [1]. Machine learning (ML)techniques for automatic diagnosis have lately acquired appeal in the medical field, becoming an additional tool for physicians. Deep learning (DL), a prominent area of study on artificial intelligence, allows the development of models that accomplish promised outcomes with input data without the requirement for human extraction of features. Deep learning methods have been used effectively to various issues, such as the identification of rhythms. Classification of skin cancer, breast cancer detection, classification of brain diseases, chest x-ray pneumonia detection pictures, imagery segmentation, and segmentation of the lungs. The fast development of the COVID-19 pandemic has required competence in this area. This raised interest in creating AI-based automated detection systems. Because of the restricted number of radiologists, it is difficult for competent doctors to supply each institution. Simple, precise, and quick AI models may thus help overcome this issue and offer patients with immediate support. While radiologists have considerable expertise, they play a crucial role, AI technology in radiology can help get correct diagnoses. Furthermore, AI techniques can help to eliminate drawbacks such as theabsence of available reverse transcription-polymerase chain reaction (RT-PCR) test kits, test costs, and test result wait times. [2].

The remainder of the paper is structured accordingly. The corresponding work is described in Section 2. Section 3 researchmethodology. Section 4 also presents the details of experiments results and a description of benchmark data sets. Finally, the concluding remarks along with the scope for future work at the end of this paper are in Section 5.

II. LITERATURE REVIEW

The literature background is provided in this section. It shows studies linked to CT and X-ray pictures utilizing machine-learning approaches from several researchers for computerized-aided detecting coronaviral (COVID-19). Various methods have been used to identify coronavirus utilizing computer assistance.

Suggested [3]a deep learning (DL) prototype utilizing ResNet32, the Convolutional Block Attention Module. The prototype training was based on the Kaggle data set comprising CXR pictures. The ResNet32 with attention module improves the basic network efficiency by improving further designs and approaches with a precision of 97.69%. This promising, effective categorization of its proposed technique suggests that it is perfect for the classification of the CXR picture in COVID-19 detection in words of precision and cost.

Explore in this study [4]the typical frameworks of DL extraction for accurate identification of COVID-19. The essential components in learning were Xception, ResNet, InceptionV3, MobileNet, DenseNet, InceptionResNetV2, VGGNet, and NASNet selected from a pool of DNN to get the most precise characteristic. The characteristics collected were then added to a set of ML categorizations, who categorized patients as cases or controls in COVID-19. A publicly accessible COVID-19 chest x-ray and ct pictures dataset has been used for verifying the recommended approach. With a classification accuracy of 99%, the DenseNet121 feature extractor with bagging tree categorization was the finest outcome. A hybrid ResNet50 function extractor from LightGBM trained with a precision of 98 was the second-best learner.

In this paper, [5] they suggest an altered integration of two CNN constructions called Xception and ResNet50V2 to identify COVID-19 verified patients by dividing them into four groups, which makes the scheme strong by utilizing several feature extraction abilities. The suggested technique gives better exactness, accuracy, recall than F1-Score, having values of 93.412 %, 96.6 %, 99.6 %, and 98 %.The technique provided may be used as an automated diagnostic system to diagnose, verify and monitor potential COVID-19 cases utilizing clinicians and radiologists.

Presently[6], (CT), X-ray, and Ultrasound (US) pictures are manually examined for confirmation by doctors, or conduct polymerase chain reaction (PCR). In most district hospitals in Pakistan, CT scanners are employed, but in all hospitals (wide metropolitan cities), X-Ray equipment is accessible. As many automatic, time-efficient and reliable techniques to Covid-19 are needed, an automatic Covid-19 detection method was introduced utilizing CNN. All of them collected from the Radiology (Diagnostics) Department, the BVHB, Pakistan have been utilized for three public datasets and one locally accessible. In terms of mean precision (96.68%), specificities (95.65%), and sensitivity (96.24 percent), the technology presented conducted well. The model is currently available from Pakistan Radiology Department (BVHB) on a big dataset.

They work [7]on lightweight and efficient mobile DL prototypes for COVID-19 diagnosis, with US lung imaging. COVID-19, pneumonia, and health were the 3 groups participating in this work. In contrast to both current lightweight and high neural network models, the new network, known as Mini COVIDNet, was developed. With a training duration of just 24 minutes, the proposed network is 83.2 % reliable. The Mini-COVIDNet improves the accuracy and latency of other lightweight networks according to various lightweight networks on embedded devices.

The most existing [8]approach of ML is a Fibonacci Pattern-based function description with sizes. Two public data sets are used for analysis: (a) Kaggle and (b) COVIDGR. Several assessment measurements, involving exactness, a clear indication, specificity, precision, and f1 outcomes, will be utilized to assess system performance. Kaggle x-rays displayed a difference of about 100% for the three-class categorization system among normal and COVID-19 X-rays. The score for the COVIDGR dataset is 72.65 6.83, while its particular characteristics are 77.72 8.06.

The study[9] proposes the CovFrameNet framework, which includes a picture pre-processing pipeline approach & a bigger learning prototype for feature extraction, categorization, and efficiency metrology. The study's most recent accomplishment was the construction of a CNN architecture with better picture pre-processing skills. The proposed prototype has 0.1 accuracy, 0.85 reminders/precision, 0.9 F measures & 1.0 specificity according to the analysis. The results of the study demonstrate that pre-screening of suspected COVID-19 cases and validation of RT-PCR discovered COVID-19 cases may be done using a CNN approach based on imaging pre-processing abilities.

III. RESEARCH METHODOLOGY

This section concentrates on the explanation of the issue and the way to solve it using the methodology provided. our study method and flow diagram are suggested.

A. Problem Statement

COVID-19 has become a global health catastrophe since December 2019. WHO identified this disease as a pandemic; these countries' health officials are always trying to restrict viral propagation by emphasizing regulations on masks, social distance as well as cleanliness? Prior diagnosis of COVID-19 may reduce the chance of the patient becoming killed, particularly in cases when no visible signs occur. It has been shown out to be essential to test and isolate carriers of this virus. A Polymerase Chain Reaction (PCR) throat swab test is now applied for screen people, having a sensitivity of 99 percent & a specificity of 98 percent if correctly performed. But every nation's testing capability remains a problem. A true danger to humanity has been the novel COVID-19 virus. This article shows a show of idea premise that COVID-19 patients infected with their X-ray chest picture may be identified. To address the issue, these difficulties may be solved and the essential characteristics can be removed from subscales. There are no statistics connected to Covid-19, which is a major issue.

B. Proposed Methodology

To solve the above-given problems, in our study, we utilized three different data sets. The pictures were collected from several sources in each data set. Data must be refined before working on data so that it can be easily handled. This study investigated the role of machine & image processing to speed and accurately identify three COVID-19 public data sets, consisting of five essential stages: data gathering, pre-processing, functional extraction, dimensional decrease, and categorization. HOG and LBP were used to extract features. By using multiple linear regressions, we developed a method of feature importance. In addition, the 10-fold cross-validation technique was used with the CNN Alextnet prototype during the classification phase.

1) Data Preprocessing

To decrease noise in CT images, a preprocessing step is performed. The first stage in the pre-processing procedure is to convert all pictures to grey. This procedure was done by the need for pictures to run the computer application in comparable formats. In addition, this procedure was not successful and the cost and duration of transactions substantially decreased. The picture sharpening procedure was used during the pretreatment step to make the picture sharper and better for success. The picture resizing, image transformations & image sharpening algorithms are executed at pre-processing step.

2) Feature extraction & dimension reduction

Feature extraction decreases the dimensionality of data where informational and non-redundant characteristics are utilized to analyze data that can also be interpreted by humans. In this study, the method of feature extraction is termed an oriented gradient histogram and LBP. In the function extraction stage of our research, HOG and LBP techniques were used. For these four distinct methods, HOG and LBP have been most effective. Therefore, in the following section of the study, the findings of HOG and LBP are provided. Features have been extracted for classification. The extraction methods have been discussed briefly in the next sections.

- **Histogram of Oriented Gradients (HOG)**

Oriented Gradient Histogram is a descriptor feature like the Canny Edge Detector (SIFT) HOG (Scale Invariant and Feature Transform). It is used in computer vision and image processing for object detection. The method includes examples of gradient orientation in the area of a picture. The HOG descriptor concentrates on an object structure or form. The magnitude and also angle of the gradient to calculate the characteristics are superior to any border descriptors. It produces histograms utilizing the magnitude and the direction of the gradient in the areas of the picture[10].

- **Local Binary Patterns (LBP)**

The LBP is an effective technique for extracting texture features. This technique is extremely popular for the identification of faces and patterns recognition methods. The LBP operator converts a picture into an array of pictures of integer labels, which defines the tiny image appearance. LBP descriptors capture local spatial patterns and grey contrast in a picture effectively. The pixel values in the segmented pictures in LBP are contrasted to the center pixel value for a threshold calculation[11][12].

3) Feature Importance by Multiple Linear Regression

The main feature relates to methods that give a score to inputs depending on how helpful a target variable is to forecast. Multiple linear regression refers to a statistical method used to predict the value of a variable based on 2 variables or more. It is sometimes simply known as multiple regression and is a linear regression extension. The variable that we are trying to forecast is known as the variable depending, while the variable used to estimate the value is known as the independent variable or the explanatory variable.

4) K-fold Cross-Validation

Thistechnique enhances the method of a holdout. The variance of the resultant estimate is decreased. The data set for the training is split into K random subgroups containing equal data. For each of these K subsets, the holdout technique is frequent K times. Every time a test set is utilized by one of the K subsets, and other K-1 subsets are used to train a model. Cross-validation validity is reported by precise measures like ROC AUC, precision and F-Score so on[13].

C. . Exiting SVM Approach

Support Vector Machine (SVM) is a strong supervised model for learning that enables an excellent marginal categorization in non-linear functional environments. This may be achieved by maximizing the working and geometric margins of the chosen hyperplane of choice. SVM may be used for both issues of regression and classification. By using the kernel trick, SVM may be utilized as both a linear and a non-linear classifier. The main aim of SVM is to increase the range so that the patterns can be corrected, i.e. the greater the range, the better the patterns are categorized [14].

D. Proposed Approach

CNN is a common kind of deep neural network in Deep learning. CNN does not require to extract manual functions such as conventional extraction methods, such as HOG, LBP, and so forth. A collection of picture data is extracted directly by CNN. Related characteristics are not pre-trained; they are learning when a collection of pictures is in the train. Traditional machine learning methods to a manual extraction and the classification algorithm independently categories the items. However, as deep learning approach the network itself, it also classifies objects without interpreting the customer. Examples include LeNet, AlexNet, VGG Net, NiN, and all other models which are convolutionary (All Conv).

Convolutionary neural network built to fulfill the task of categorization of pictures using various layers. The CNN construction includes the following layers[15]:

- **Input Layer:** This input layer receives raw pictures and is passed for features extraction to further layers.
- **Convolution Layer:** The layer following the input layer is the next layer. This filter layer applies to pictures to discover characteristics from pictures. These functionalities are utilized in the testing process to estimate matches.
- **ReLU (Rectified-Linear Unit):** After a layer of convolution, the next layer is the linear rectified unit ReLU. This layer substitutes the negative convolution layer no. with 0 which helps to improve the training quicker and more efficiently.
- **Pooling:** Removed functionality is transmitted to the pooling layer. This layer collects and lowers big pictures and decreases the parameters to maintain essential information. The highest values of every window are preserved.
- **Fully Connected Layer:** The last layer is a fully connected layer that captures filtered pictures on a high level and converts them into categorized labels.
- **Softmax Layer:** This layer is introduced just before the output layer. This layer gives the decimal chance for every class. The chance is decimal between 0 and 1.

a) AlexNet Model

In 2012 Alex Krizhevesky et al. presented a more extensive CNN model than LeNet and was the 2012 ILSVRC challenging ImageNet challenge to be able to identify visual objects. With all conventional ML & computer vision approaches, AlexNet obtained state-of-the-art recognition accuracy. It was a great accomplishment in visual identification and categorization in ML with computer vision as well as history if an interest in DL has grown fast.

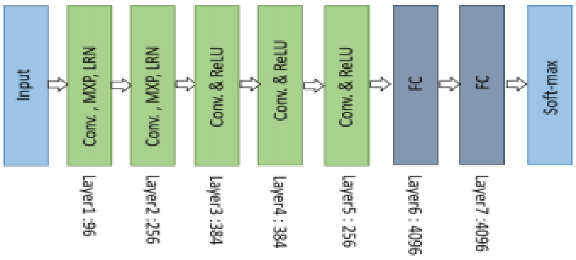


Figure 1 AlexNet architecture: Convolution, max pooling, LRN, fully connected layer (FC)

Fig. 1 illustrates the structure of AlexNet. The 1st convolutional layer is converted & max pooled with LRN (Local Response Normalization) where 96 distinct receiving filters of the size of 11×11 are employed. The maximum pooling procedures are conducted with 3×3 filters of 2 step sizes. In the 2nd layer, identical procedures with 5×5 filters are carried out. different filters with 384, 384, and 296 map functions, are employed in the third, fourth, & fifth convolution layers. The end is followed by a softmax layer and two FC layers are utilized with drop out. This model is being trained in parallel for two networks with a comparable architecture and the same amount of feature maps. This network presents two novel concepts, the Normalization of local response (LRN) and dropout. LRN could be used in two ways: firstly, to deploy the N×N patch from the same map to single-channel or feature maps and normalize one neighborhood. Second, LRN may be utilized on channels or map features (third-dimensional neighborhood but only a single-pixel or location).

E. Proposed Algorithm

Step 1- Three data set loading (CT, X-ray & CT).

Step 2- Resizing, RGB to Gray, picture Sharpening Pre-processing.

Step 3- Extraction of Feature.

1. Put on HOG
2. Rub on LBP

Step 4- Dimensionality Reduction utilize multiple linear regression.

Step 5- Classification

1. Put on CNN Alexnet Model.
2. Put on 10-fold cross-validation.

Step 6- Matrices for performance assessment;

Step 7- Corona virus detection Otherwise if yes then proceed to step 8 go to step 1.

Step 9 – Images predicted.

F. Proposed Flowchart

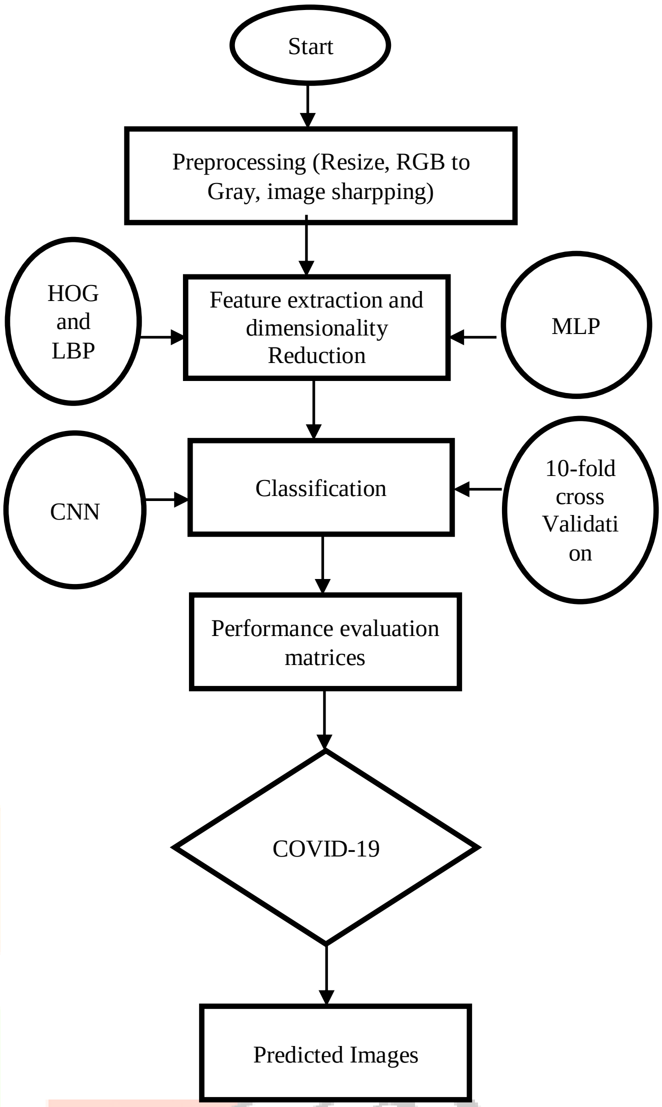


Figure 2: Flowchart of Proposed Model

IV. RESULTS ILLUSTRATIONS

In this section, the dataset description, metrics, parameters, and experimental results are introduced. This proposed work has experimented using the language of python programming as well as the platform is Jupiter notebook. The results of the experiment are presented in several graphs and metrics or tables. We shall examine the results of the experiment in depth in the subsequent.

A. Dataset Description

In our research, three distinct data sets were utilized. The pictures were collected from several sources from each data collection.

Our first dataset consists of CT scans. It contains 349 pictures of 216 Covid-19 patients and 397 pictures of Covid-19 (-). While 169 individuals are old, 137 persons have gender info. While 37% of people with COVID-19 (+) are women, 63% are men[16].

Another type of data is made up of X-ray pictures. The data collection contains 125 positive pictures to COVID-19. Forty-three of these images are ladies, of which 82 are men. Furthermore, there are 500 pure lung X-ray pictures without abnormalities & 500 infection pictures but not

COVID. This was produced via the grouping of mages from numerous research data sets. There is no comprehensive data set available. The data set contains 26 positive data with age limits and an average of 55[16].

Our 3rd and last data set are a CT scans data set with far more views than our two prior sets of data. The data set generated by the research number comprises a public COVID-19 CT scan dataset including 1252 COVID-19 (+) CT scans & 1230 COVID-19 CT scans, respectively (-). Patients in Sao Paulo, Brazil provided data collection. The pictures in the data set include 60 persons in total, 32 of them male and 28 of them female. Although COVID-19 (+) is 30 of them, the remaining 30 individuals are negative. In addition, there is no further information about the data in the research[16].

B. Performance Metrics

Performance metrics are required to compute the experiment result for the categorization models. There may be many performance measures to reflect the result of the categorization. Performance metrics are being used to assess the quality of the learning model. Several different kinds of evaluation measures may be used to test a prototype. These include classification accuracy, matrix confusion, and others. The confusion matrix is a matrix used to predict the efficiency for a certain number of test data of the classification models. The matrix itself is easy to understand, but the terminology associated with it may be confusing.The True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) data have been evaluated using a confusion matrix. The clinical significance of a test may be seen as a positive predictive value (PPV) and negative (NPV) predictive value. The major distinction between sensitivity and specificity between PPV and NPV is that they are prevalent. The proportion of true positive is sensitivity. Specificity is the proportion of genuine negatives. Precision is the rate that can properly identify all people with and without the illness.

1) Accuracy

Accuracy represents the total accuracy of the model. The effectiveness of different ML models or algorithms is useful to evaluate. The ratio of total no. of correctly categorized tasters over the overall no. of samples is named accuracy. It can be mathematically defined for the binary classification problems as follows:

$$\text{Accuracy} = \frac{TP + TN}{\text{N}}$$

2) Precision

Precision is measured as the fraction of genuine positive instances in the total positive cases. (a true positive + false positive). It is the ratio of correctly predicted images to the total no of images to categorize.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

3) Recall

It is the proportion of cases belonging to the positive class, which are properly predicted. It is sometimes referred to as sensitivity or true positive rate.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

4) F1-Score

It is the harmonic mean of the precise & recall model. It is the metric to assess predictive accuracy as a statistical measure.

$$\text{F}_\beta = \frac{(1 + \beta^2)(\text{Precision} - \text{Recall})}{\beta^2 * (\text{Precision} + \text{Recall})}$$

5) Sensitivity

It measures the percentage of positive real instances that are shown to be positive (or true positive). It is also known as a recall. This implies that another percentage of positive instances are incorrectly judged to be negative (and, thus, could also be termed as the FN). This may also be shown as an FR rate.

$$\text{Sensitivity} = \frac{TP}{\text{TP} + \text{FN}} = \frac{TP}{P}$$

6) Specificity

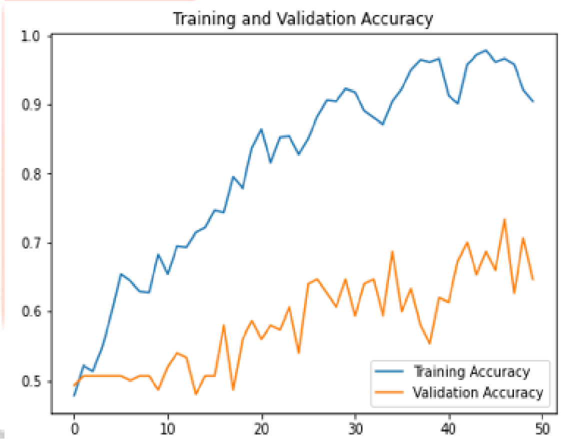
The TN ratio is calculated as negative (or TN). This means that a proportion of the real negatives, which might be termed FP, is expected to be positive. Sometimes this fraction is referred to as FR rate.

$$\text{Sensitivity} = \frac{TN}{\text{TN} + \text{FP}} = \frac{TN}{N}$$

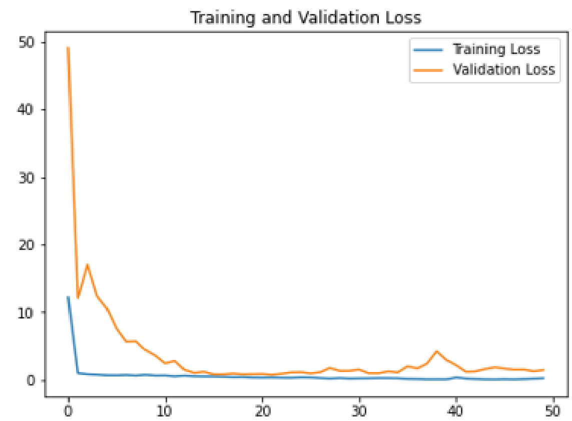
C. Experimental Results

The examination of each of the metrics included in the practical and also recommended solution was carried out in the experimental tests carried out. In this section, we present the suggested result with a different- different dataset.

1) Results of Dataset-1



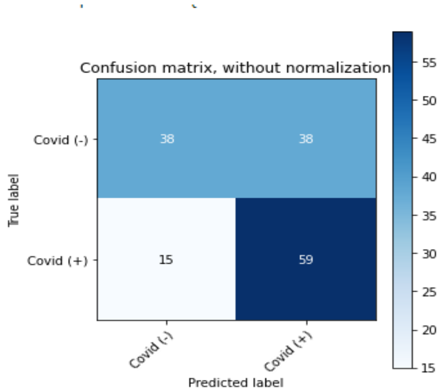
(a)Accuracy of training and validation



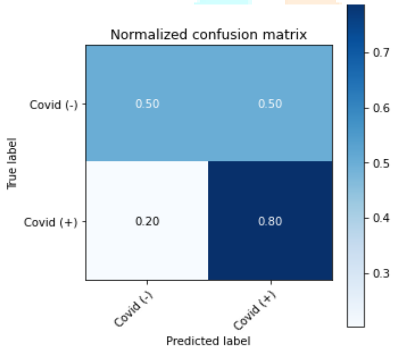
(b)Loss of training and validation

Figure 3: Training plot and accuracy of validation and loss of the Alexnet model for Proposed

The above figure 3 shows the accuracy and loss graph of the Alexnet model. Based on the above outcomes, the CNN algorithm can provide superior plant picture outcomes after Fifty epochs. This first dataset obtains better accuracy compared to the exiting SVM method. Alexnet model given 91.62% accuracy from CT image dataset. Also in this graph shows the training and validation lossin the starting of highest accuracy and loss as the iteration increases then curve of the training and validation loss decreases.



(a) Confusion Matrix without normalization

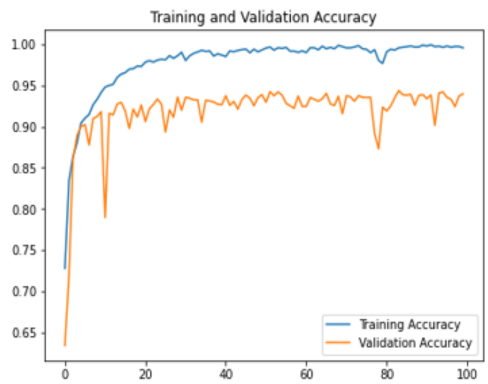


(b) normalization of Confusion Matrix

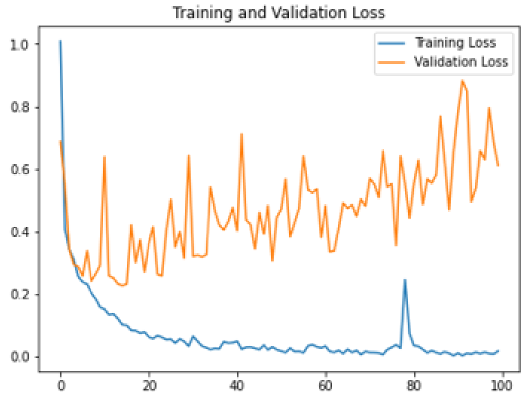
Figure 4: Using ALEXNET model with and without normalization confusion matrices

The CNN Alexnet model's confusion matrices for COVID-19 CT scan images. Figure 4 depicts the categorization results from the preceding figure. The confusion matrices were obtained as the results of a classification method. False-positive and false-negative examples were found in the matrix of confusion.

2) Results of Dataset-2



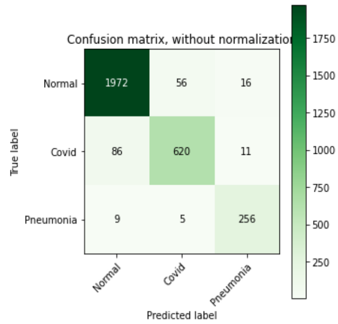
(a)accuracy of Training and validation



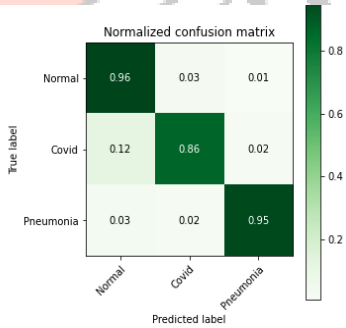
(b) Training and validation loss

Figure 5: Plot of Training and validation accuracy & Loss of ALEXNET model for Proposed

The above figure 5 shows the accuracy and loss graph of the CNN Alexnet model. Alexnet model given 99.64% accuracy from CT image dataset. An analysis to identify the model may also be detected by a declining training accuracy that continues to deteriorate after the plot.



(a) Confusion Matrix without normalization

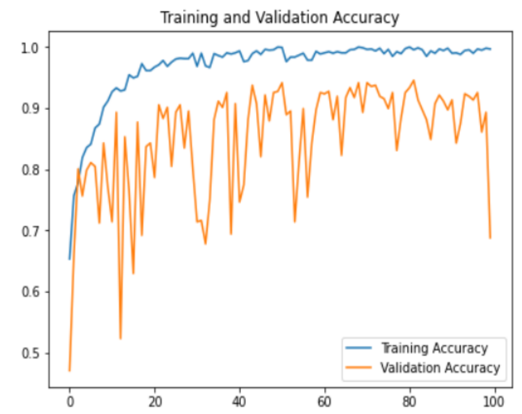


(b) Confusion Matrix normalization

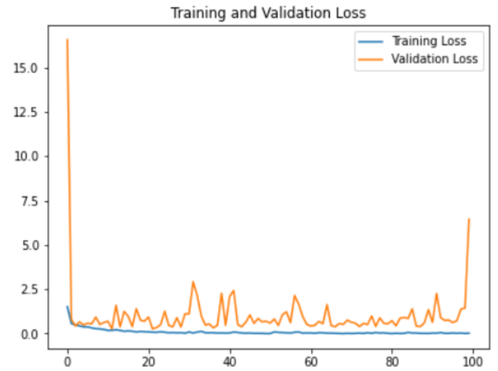
Figure 6: Using ALEXNET model with and without normalization confusion matrices

As an outcome of the classification stage, the confusion matrices were generated as shown in figure 6. The classification algorithms are extremely effective at detecting COVID-19 (+). On the other hand, it was discovered that the CNN approach gave relatively better outcomes than other techniques in the classification of both (+) and (-) data.

3) Results of Dataset-3



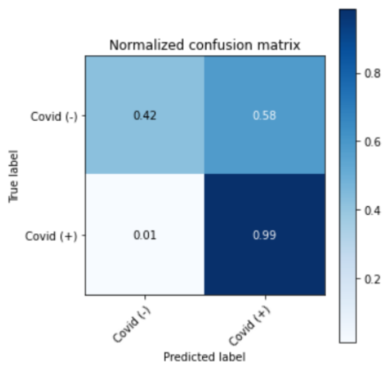
(a)accuracy of Training and validation



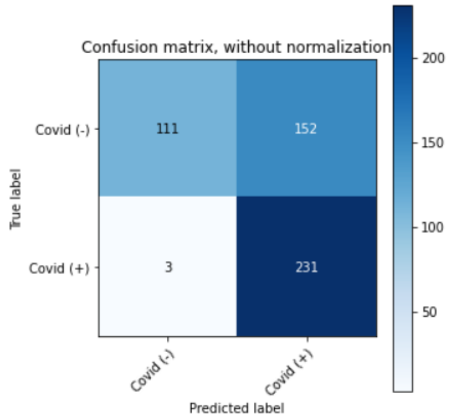
(b) Training and validation loss

Figure 7: Plot of Training and validation accuracy & Loss of ALEXNET model for Proposed

The above figure 7 shows the training accuracies versus validation precision and loss of the suggested model, and according to the preceding findings, the CNN alexnet model produces the best plant image outputs after epochs. It also increases training accuracy. The figure shows the accuracy graph of the alexnet model. This data set achieved higher accuracy 99.82% comparison to the exiting method.



(a) normalization of a confusion matrix



(b) Matrix of confusion without normalization

Figure 8: Using ALEXNET model with and without normalization confusion matrices

The CNN Alexnet model's confusion matrices for COVID-19 chest X-ray images. The categorization results depicted in preceding image are depicted in figure 8.

Table 1: Comparison of Training accuracy

Datasets	Training Accuracy	
	Exiting (SVM)	Proposed (Alexnet)
Dataset-1	87.68	91.62
Dataset-2	95.54	99.64
Dataset-3	93.25	99.82

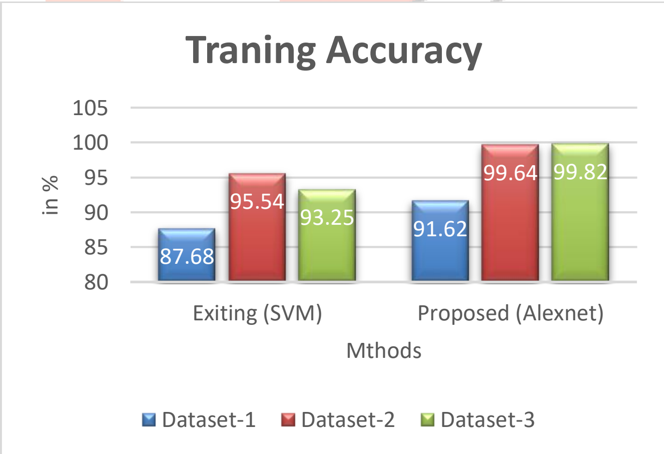


Figure 9: Comparison graph of Existing and proposed model of Training accuracy for three datasets.

The above figure 9 and table 1 show the comparison graph of the SVM and alexnet model of training accuracy for three different datasets. The dataset-1 given SVM accuracy 87.68% and proposed 91.62%. Dataset-2 given the accuracy of base SVM 95.54% and proposed alexnet model 99.64%. and the last dataset-3 given acracy of SVM 93.25% and proposed accuracy 99.82% respectively. Graph and table clearly show the proposed model given higher accuracy comparison to exiting SVM classifier from three datasets.

V. CONCLUSION AND FUTURE WORK

COVID-19 is essential in the present scenario where COVID-19 continues to spread quick and efficient diagnostic and disease evolution analyses. COVID-19 is very infectious and rapidly spread worldwide, & early identification is of dominant crucial. Computer-supported diagnostic methods to help identify positive COVID-19 instances are therefore developed and implemented. Pre-trained CNN is frequently used to identify illnesses from bigger datasets by computer. The research examines the efficiency of CNN, a mixture of multiple pre-trained CNNs, to automatically identify COVID-19 from CT scans and X-ray pictures. The suggested Alexnet Model was used on 3 separate COVID-19 public data sets & includes the 5 phases. The pre-trained CNN Alexnet model is shown through an experimental study conducted utilizing three public datasets. The suggested model executes at significant COVID-19 detection levels for data-1 (CT), data-2 (X-ray), and data-3 (CT), correspondingly, with the accuracy of 91.62% to 99.64% and 99.82%. An analysis of the patient's CT scans and X-ray images can intuitively measure illness progression and evaluate disease trends.

The future aim of our work is to build a model for comparison with DL approaches. This evaluates the effectiveness & time of implementation of both methods of deep learning and classical approaches. We will perform further explanatory models analyses, which will highlight COVID-19 detecting mechanisms, identify essential features of CT pictures and ease screening by clinicians. While the system is performing well with publicly available datasets, the study is yet theoretical and the models have not been verified in actual clinical practice.

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