IDENTIFICATION OF COVID USING CNN

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***Abstract*—The COVID-19 epidemic that occurred in late 2019 has challenged the global health situation of the public economically and socially. The rapid spread has caused panic in the public and an accurate diagnosis was required to control the spread of the virus and efficient usage of resources. The main mode of transfer of this virus from one individual to another was by air. Virus was mainly transmitted when the people breath in air that was containing small air particles that contained the virus that was released by the people already effected by the virus. It has been determined that the expanding field of artificial intelligence is a potent instrument to improve diagnostic procedure. This study aims to demonstrate the effective usage of Convolutional Neural Networks (CNN) in identification of the presence of virus from chest X-ray image datasets. This technique offers a fast and accurate solution. Thousands of chest radiation pictures form a big dataset that is used to train a CNN-based model. To increase forecast speed and accuracy, the model has undergone extensive testing and validation procedures. Additionally, the model demonstrated how to evaluate the severity and course of infections, which aided in patient planning and differentiation to stop the virus from spreading. By different AI- driven tools like the proposed CNN model has enhanced the accuracy of diagnosis, efficiency and increasing a proper response to the disease outbreak. So many approaches have been developed using deep learning to identify and detect the traces of the virus. It has been demonstrated that Convolutional neural networks are extremely effective when utilized for image analysis and classification. Our COVIDCX-Net model attains an increase in the accuracy by +0.48 percentage than the existing models.**

***Index Terms*—Covid, Convolutional Neural Networks, Computuer Topography, COVIDCX-Net.**

I. Introduction

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, has resulted in widespread fatalities and healthcare crises worldwide. Due to its airborne transmission and delayed symptoms, early diagnosis is crucial in controlling its spread. [1] Researchers have leveraged Convolutional Neural Networks (CNNs) to develop automated diagnostic systems using chest X-ray and CT scan images. CNN models process these medical images to identify COVID-19 infections with high accuracy, reducing dependency on costly and time-consuming lab tests. [2] However, these models face challenges due to limited and imbalanced datasets, leading to potential inaccuracies. To overcome this, data augmentation techniques are employed to improve training data diversity and model robustness. [3] CNN-based methods like COVIDCX-Net have demonstrated superior performance by incorporating additional convolutional layers. These models have significantly improved the speed, accuracy, and accessibility of COVID-19 diagnosis, making them a valuable tool in mass testing and medical decision-making. [4]

COVIDGAN plays a crucial role in addressing data scarcity by generating synthetic chest X-ray images of COVID-19 patients. [5] By expanding the dataset, it enhances machine learning models' ability to classify and detect infections more accurately. Another key advancement is SD-Net, which refines CNN performance by applying selective domain normalization to medical images. [6] This technique ensures that different domains within an image are normalized separately, improving diagnostic precision. [7]By integrating CNNs, GAN-generated images, and domain-specific normalization, the COVID-19 detection process becomes more efficient and reliable. [8] These innovations have led to the development of high-performing diagnostic models, reducing false positives and improving healthcare outcomes. [9] With deep learning-powered image processing, automated COVID-19 identification is now faster and more accessible, making it a crucial advancement in pandemic response and medical imaging research. [10]

II. II.LITERATURE SURVEY

Deep learning has revolutionized numerous fields, particularly in medical imaging, where its application has proven invaluable in disease detection. COVID-19, a highly infectious disease caused by the SARS-CoV-2 virus, significantly impacted global health. [11] The role of deep learning, especially Convolutional Neural Networks (CNNs), in COVID-19 diagnosis has been extensively explored. Several artificial neural network (ANN)-based and deep learning models have been developed to detect COVID-19 using chest X-rays and CT scans. [12] CNNs have excelled in image analysis due to their ability to extract essential features automatically, leading to improved accuracy in detecting anomalies . The challenge in training these models effectively stems from the availability of diverse and well-annotated datasets. [13] Researchers have employed various augmentation techniques such as flipping, rotation, and cropping to enhance dataset variability. Additionally, due to limited COVID-19 image datasets, Generative Adversarial Networks (GANs) have been employed to synthesize high-quality artificial medical images, thereby improving model robustness and performance. [14] COVIDGAN, a GAN-based model, has been instrumental in supplementing existing datasets to improve classification accuracy . The datasets collected from sources like GitHub and Kaggle have undergone extensive pre-processing, including noise reduction and edge enhancement, to refine image quality for deep learning models. [15]

To further enhance COVID-19 detection, hybrid approaches integrating CNNs with domain selection techniques such as Image SD-Net have been explored. [16] SD-Net employs domain-specific statistics to normalize image features, improving model generalization across different datasets. The adoption of deep learning-based models such as DeTrac has enabled the identification of COVID-19 features with high precision. [17] DeTrac employs a deep transfer learning approach where a pre-trained CNN model is fine-tuned with COVID-19 data to enhance classification accuracy. Another crucial aspect of CNNs is the pooling layer, particularly max pooling, which aids in the extraction of sharp and significant image features. [18] Studies have demonstrated that increasing convolutional layers within CNN models enhances COVID-19 detection accuracy by capturing intricate image patterns. [19] The COVIDCX-Net model, which integrates additional convolutional layers, has been shown to outperform conventional CNN models in detecting COVID-19 from X-ray images. Moreover, employing binary cross-entropy loss functions in CNN architectures has resulted in improved classification performance. [20]

Data augmentation remains a vital technique in medical image processing to expand limited datasets, ultimately enhancing deep learning model performance. Augmentation methods, including noise addition, contrast enhancement, and synthetic image generation via COVIDGAN, have contributed to model efficiency. [21] The COVID-19 detection models have significantly benefited from transfer learning, wherein pre-trained networks such as ResNet, DenseNet, and VGG are fine-tuned with COVID-19 datasets. [22] CNN-based models integrated with advanced feature extraction methods have outperformed traditional machine learning approaches, enabling quicker and more accurate diagnoses. [23] Moreover, balancing dataset classes through oversampling and undersampling techniques has improved classification results, ensuring fairness across different patient categories. Studies indicate that applying deep learning in radiology can aid in mass COVID-19 screening, reducing reliance on conventional testing methods. [24] CNN architectures designed for COVID-19 identification have been tested across multiple datasets, demonstrating their robustness in clinical settings. [25]

The effectiveness of CNN-based COVID-19 detection is further strengthened by integrating domain adaptation techniques. Image SD-Net has been crucial in addressing domain shifts in medical imaging, improving generalization across different datasets. [26] Recent studies suggest that deep ensemble learning methods, which combine multiple CNN models, offer superior performance by reducing overfitting and enhancing prediction accuracy. [27] To ensure reliable results, researchers have developed frameworks that evaluate model robustness against adversarial attacks, securing CNN-based medical diagnostic systems. [28] The rapid advancements in deep learning for COVID-19 identification highlight the potential of AI-driven solutions in pandemic response, paving the way for future innovations in automated medical diagnostics. [29] The integration of CNNs, COVIDGANs, DeTrac, and Image SD-Net continues to shape the landscape of medical imaging, facilitating early disease detection and effective healthcare interventions. [30]

III. PROPOSED WORK

We developed a model and named it COVIDCX-Net model as it works on the chest radiation pictures to determine whether a person has COVID-19 or not. In this model we are going chest radiation pictures dataset which consists of two classes of images they are covid and normal classes holding a total of 1726 images. The images are further classified into training and validation classes through which input the chest radiation pictures can be trained and validated against the model outcomes are computed to determine the accuracy and losses.

A. Data Description

After the picture dataset was loaded, there were seminars for training and validation photos, 1726 photos in all were made available, 1381 of which were designated for training, 345 chest radiation pictures are provided to validation belonging to the covid affected and normal classes such as in Fig. 1. Images are sorted into two groups, such as train and validation, which are then further divided into covid and normal classes. The images from the covid dataset, which includes both normal and covid-confirmed chest and resized

Fig. 1. Sample Input Image.

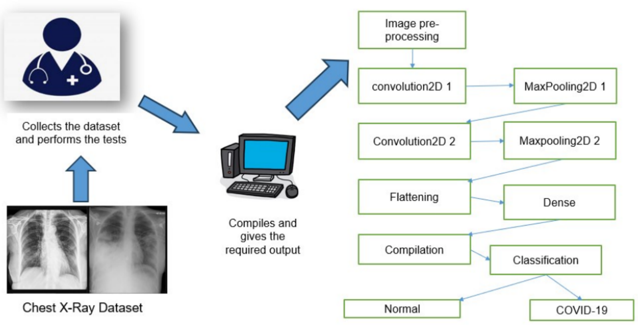

Fig. 2. Archiecture diagram of COVIDCX-Net

in accordance with datset's specifications.

This section explains about the COVIDCX-Net model and our approaches we employ to apply them to the early identification of COVID-19 and its detection and to analyze the virus and its performance. Here in the COVIDCX- Net model we are going to import all the necessary libraries to load the image, classification and processing of the dataset of the chest radiation pictures.

At first all the necessary libraries such as tensorflow, os, numpy, pandas, cv2, keras, imagedatagenerator and the models such as sequential, models are being imported. Layers such as Conv2D, MaxPooling2D, GlobalAveragePoolong2D, activation, Dropout, batch normal- ization , flatten, Dense, AvgPool2D layers have been imported in our model to calculate the performance as in the Fig 2.

The dimensionality of the dataset necessitated the use of data augmentation in the experiments despite pre- training in order to prevent overfitting and boost quantity of training samples. Data augmentation is applied to the dataset in order to expand its size and provide more images, which enhances the model's performance. Specifically, several scaling config-

Fig. 3. Preprocessed Image

urations involving horizontal flipping operations are incorporated into the training process to accommodate the possible outcomes provided by the broad range of acquisition device diversity and the symmetrical feature of the human body.

B. *Algorithm*

Step1 : Let be output label and let be input picture for actual chest radiation pictures

Step2 :The outcome for output label y could be COVID-19 or normal.

Step3 :The preprocessing step involves modifying height and width of chest radiation pictures.

Step4 :Phase of training: for the steps in training iterations:

(i) Mini batch sample of noise sample,...,derived from the noise before.
(ii) An example mini batch from the data creation distribution is example,....
(iii) The discriminator receives a transmission of the actual picture. Using the transfer model, the discriminator is updated by climbing its stochastic gradient. conclude for
(i) Noise prior is sampled to create a mini batch of m noise sample,...,.
(ii) Sliding its stochastic gradient updates discriminator.
conclude for
Step5: Phase of testing: production label is created. The preprocessed image is as in Fig3

Next, we apply the model to the dataset and include Conv2D, Maxpooling2D and activation layers are added to the dataset along with Dense, Flatten, Dropout, the sigmoid and RELU activation layers are being used in the model. The total number of parameters that are available to 6,33,435 parameters and the number of trainable parameters are 6,33,435 parameters are being trained in the dataset. In this model, there

TABLE I
PERFORMANCE METRICS FOR DIFFERENT MODELS

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
VGG-16	87.5	85.0	85.0	85.0
VGG-19	90.0	87.0	87.0	87.0
ResNet-34	94.0	91.5	91.5	91.5
DenseNet-121	90.0	87.5	87.5	87.5

are no non-trainable parameters, the class mode we used is binary for both the training and the validation splits. Total no of epochs used in model are 48 epochs and each epoch layer consists or performs 201 steps to provide the input chest radiation picture's loss, validation loss, accuracy and validation accuracy.

IV. RESULT ANALYSIS

The accuracy of different models are shown in the tableI below Output of model is shown in the graphs, the graph represents the values of loss, accuracy, validation loss, validation accuracy. There is an improvement in the performance of the accuracy and the validation loss has been reduced. The pre-trained images are being classified and divided into two separate classes train and test, to train, the train datasets are utilized. chest radiation pictures and test dataset is used for testing those images of the chest x-ray against our COVIDCX-Net model to acquire outcomes, view performance, and evaluate outcomes.

Total number of images that are used in this dataset is 1726 images and it has been divided into two classes they are training class and test class, the train class is provided with 1381 images whereas the test class has 345 images. In order to obtain a higher accuracy with better performance the images have been augmented in order to create multiple images of the same image which are useful in clear identification of the cavity of covid virus in chest radiation pictures by processing images of different angles with different inputs.

The parameters are used in the model to analyze the performance, the total number of the parameters that we have used in this model is 6,33,435 parameters, and we have trained all 6,33,435 parameters in our COVIDCX-Net model, we applied 48 layers of the epochs in our model and each epoch layer has 201 steps in it. We have assigned 1209 images of 517 photos from two classes for model validation, and the two classes for training chest radiation pictures of patients affected by covid and non-covid patients chest radiation pictures.

With the help of the graphs, the output of the model is displayed. We were able to create two graphs that display the model's accuracy and loss. Model accuracy graph in fig 4() displays accuracy was around 75 percentage at first after the model is applied at first the accuracy dropped suddenly but after execution of some of the epochs and when we compare to the last we can clearly see the increase in model's accuracy.

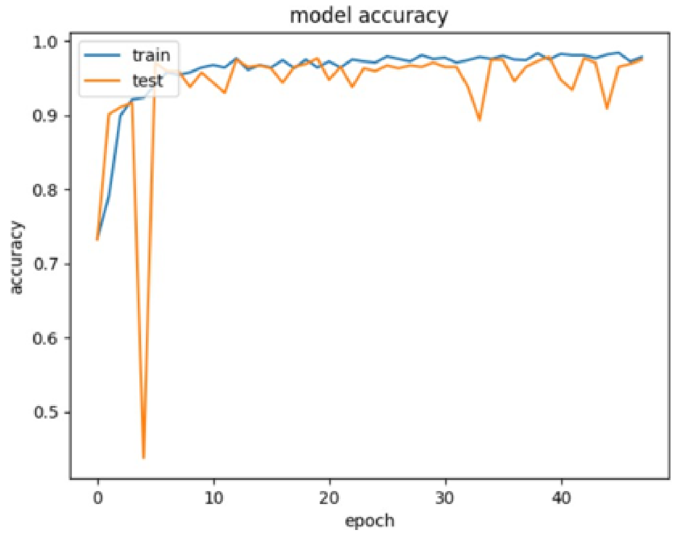

Fig. 4. Accuracy of model

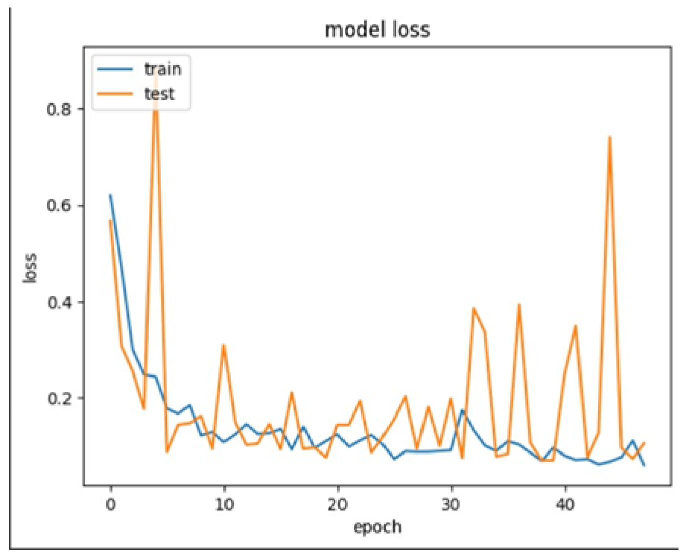

Fig. 5. Loss of model

Model loss plot displayed in fig5 has the losses reducing and increasing abruptly without maintaining consistency or is not constant but at the end we can see the loss is minimized .

Training accuracy results that we have acquired 97.83 percentage and the results of the validation accuracy we have obtained is 97.48 percentage.

C. A. Equations

The COVIDCX-Net model, image categorization and detection system, is evaluated based on four key results: actual favorable (w), bogus favorable (x), actual unfavourable (y), and bogus unfavourable (z). System performance is determined by how well following measures, which have been suggested, perform: Accuracy is required to appropriately di-

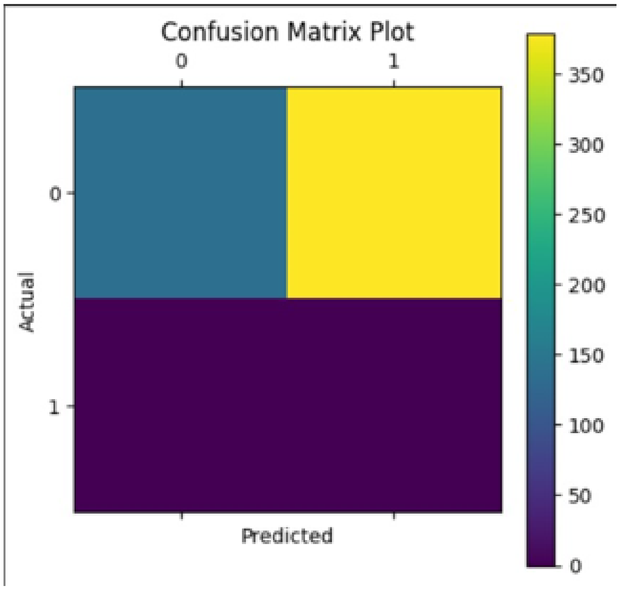

Fig. 6. Confusion Matrix

vide the various images of COVID. By calculating the ratio of true positive and negative, on the other hand, is a result where in model accurately forecasts negative. When model guesses favorable class wrongly, an x happens, equation 1 gives accuracy formula and equation 2 reveals precision formula when the model forecasts unfavor- able inaccurately, resulting in outcome of z, equation 3 shows precision formula and equation 4 derives the F1 formula.

$$accuracy = w + x/(w + x + y + z) \quad (1)$$

$$precision = w(w + x) \quad (2)$$

$$recall = w/(w + x) \quad (3)$$

$$f\,1 = 2 \;\; [(P \;\; R)/(P + R)] \quad (4)$$

The confusion matrix in Fig6 obtained from the COVIDCX-Net is as shown below: The COVIDCX-Net gives an accuracy by an in- crease of 0.48 to 0.50 percentage than the existing convolutional neural network models, the increase in the accuracy is obtained by training the model with 48 epochs which gives an increase in the accuracy but there is an decrease in the validation loss but it slightly increased at last and it again reduced without affecting the overall accuracy and performance of the model. Hence the COVIDCX-Net shows an improvement in the performance and accuracy and the existing convolutional neural networks model.

V. Conclusion

The recently discovered severe acute respiratory syndrome coronavirus is straining healthcare systems all around the world due to its rapid expansion. It is crucial to identify suspects quickly, test them, and maintain surveillance over them in order to prevent the virus's spread. Additionally, in light of this worldwide health crisis, x-ray pictures serve as the initial and major radiological method of investigation since they are more successful in isolating infected patients. Nevertheless, x-ray acquisition is faster, more convenient, and less costly than CT. However, x-ray acquisition is less expensive, more accessible, and takes less time than CT. The COVIDCX-Net model provides the output with more accuracy than the existing convolutional neural network models, this model attains an increase in the accuracy by +0.48 percentage than the models that are available till now which are having the accuracy ranging from 93 to 97 percentage based on the inputs provided and the number of the epochs that are trained. Hence our model is used to attain a slight increase in accuracy. Training accuracy results that we have acquired 97.83 percentage and the results of the validation accuracy we have obtained is 97.48 percentage. Our model gives an increase in the accuracy of 0.48 to 0.50 percentage than the existing convolutional neural network models such as densenet, resnet. There is an overall increase in accuracy and performance of the model. Therefore, the COVIDCX-Net shows an improvement in the performance and accuracy.

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