SJIF Impact Factor(2024) : 8.402
ISI I.F.Value : 1.188

ISSN (Online): 2455-3662
DOI : 10.36713/epra2013

I
J
M
R

EPRA International Journal of

MULTIDISCIPLINARY RESEARCH

Monthly, Peer Reviewed (Refereed) & Indexed International Journal

Volume - 10 Issue - 5 May 2024

ISSN (Online) : 2455 - 3662
SJIF Impact Factor(2024) :8.402
ISI I.F. Value : 1.188
DOI : 10.36713/epra2013

EPRA International Journal of Multidisciplinary Research

Monthly Peer Reviewed & Indexed
International Online Journal

Volume: 10 Issue: 5 May 2024

Indexed By:

Crossref

doi

Google Scholar

INTERNATIONAL Scientific Indexing

TOGETHER WE REACH THE GOAL

Published By :EPRA Publishing

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 5| May 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402 || ISI Value: 1.188

DECODING COVID-19: HARNESSING CNN MODELS FOR CHEST X-RAY CLASSIFICATION

Prekshith C R[1], Dr. K. Vijayalakshmi[2]
[1]*School of Computer Science and Application,REVA University, Bangalore, India*
[2]*School of Computer Science and Application, REVA University, Bangalore, India*

Article DOI: https://doi.org/10.36713/epra17041
DOI No: 10.36713/epra17041

ABSTRACT

COVID-19 is a new virus that infects the respiratory tract of the upper respiratory system and organs. Based on the worldwide epidemic, the number of illnesses and deaths was growing every day. Chest X-ray (CXR) pictures are beneficial for monitoring lung diseases, especially COVID-19. Deep learning (DL) is a popular computing concept that has been widely used in medical applications. Efforts to automatically diagnose COVID-19 have been beneficial. This study used convolution neural networks (CNN) models to develop a DL technology for binary classification of COVID-19 using CXR pictures. By reducing the number of layers and tweaking parameters, training time was reduced. The suggested model for training loss of 0.0444 and accuracy of 98.53%. In validation it demonstrates even higher proficiency attaining a loss of 0.0181 and accuracy of 99.17%. These findings highlight the need of using deep learning (DL) for early COVID-19 diagnosis and screening.

KEYWORDS*— CNN, COVID-19, X-ray, Model, Deep convolutional neural networks.***

I. INTRODUCTION

Coronavirus has emerged as a global medical issue. Pursuant to current World Health Organization statistics, the number of ill people and fatalities is steadily growing. As of this writing, the illness has claimed the lives of nearly 1.26 million people. Several Artificial Intelligence experts have offered frameworks and tactics to predict the progress of the virus and identify the condition. Chest X-ray pictures can be analyzed to determine a patient's COVID-19 infection status. In hospitals, traditionally processing large numbers of X-ray images can be time-consuming and complex.

COVID-19 is mostly spread by personal contact with infected individuals, Commonly utilized for managing this ailment are antibiotics, antimalarial drugs, antipyretics, cough suppressants, and analgesics, whether through inhalation, tactile contact, or mucosal interaction. The decision to hospitalize the infected patient is based on their illness status, symptoms, and severity [2]. The COVID-19 virus continues to spread globally. The World Health Organization (WHO) reported 3,128,962 fatalities till April 28, 2021. Early detection and treatment are crucial for preventing or minimizing the impact of pandemics on the health system.

The real-time RT-PCR method is often used to detect COVID-19. Chest radiology Early stages of COVID-19 are best diagnosed utilising techniques for imaging that involve CT and X-ray. Computed tomography provides comprehensive pictures that includes our bones, organs, soft tissue, and blood vessels. This allows doctors to distinguish interior structures, their forms, sizes, densities, and textures, as well as any damage that has occurred. CT pictures provide a precise slice of a specific body location, whereas conventional X-Rays encompass the complete body structure. The resulting body slice provides a thorough perspective of the patient's condition.

We pre-processed and trained X-ray scans from the Kaggle data pool for categorization, including Normal and COVID-19 images. X-ray imaging is a low-cost way to diagnose lung infections and identify coronaviruses. X-ray scans of COVID-19 patients show patchy infiltration or opacities similar to viral pneumonia symptoms'-rays during the early stages of COVID-19 showed no abnormalities. COVID-19 causes unilateral patchy infiltration in the middle, upper, or lower zone of the lungs, with occasional consolidation as the illness advances.[4]. Deep CNN has been utilized to address a variety of issues, including skin cancer, pneumonia, brain tumors, arrhythmia, Covid-19, image classification , lung segmentation, and breast cancer. Abbas and Abdeslam [10] employed a deep neural network dubbed Transfer, Decompose, and Compose in their study, aiming to classify COVID-19 cases according to a chest X-ray imagery. The authors recommended incorporating a class segmentation layer into previously trained models from the picture database. This layer separated every category into several sub-classes.

Deep learning (DL) stands out as a branch of machine learning, empowering computers to independently undergo training and assimilate pertinent data. Extracting traits from extensive amounts of unstructured data [8], recent advancements in medical imaging have witnessed remarkable expansion in the application of Deep Neural Network techniques. Deep convolutional neural networks (CNN) automate feature extraction from data, allowing for this breakthrough [9].

This study uses a binary classification technique To discern the presence of abnormalities in a chest X-ray picture COVID-19 either negative or positive? The suggested architecture is trained and evaluated using the COVID-19 chest CT-scan database. Experiments demonstrate the suggested architecture's great accuracy in COVID-19 detection.

II. RELATED WORKS

Soares et al. [6] used deep learning approaches such as DNN, Resent, Google Net, VGG16, Alex Net, Decision Tree, and AdaBoost to predict Covid-19 cases. The dataset undergoes an 80:20 partitioning for examination and instruction, respectively. According to the research findings, the DNN deep learning model attained a peak accuracy of 97.38%. Endeavored to identify Cifci [7] COVID-19 utilizing the Inception-V4 and Alex Net models. The training dataset comprised 4640 (80%) CT images, while the testing set consisted of 1160 (20%) CT scans. Experimental findings showed that Alex Net outperformed Inceptionv4. Alex Net obtained a accuracy 94.74%.

Wang et al. [2] analyzed 1,119 CT images from pathogen- They discovered verified COVID-19 instances with an accuracy of 89.5%, using the Inception model and deep learning approaches. Nefoussi et al. [9] compared classic histogram equalization, constrained adaptive histogram equalization, and transfer learning models for COVID-19 detection with DL approaches. The VGG19 model combined using a customized histogram equalization that is constrained by contrast outperformed the other models in the CT scan dataset, obtaining an accuracy of 95.75%.

Kumar, S. P., et al. [10] carried out research focused on COVID-19 identification in Iran, leveraging a novel database comprising 48,260 CT scan images. Employing ResNet50V2, a 50-layer network pre-trained on the ImageNet database, the research achieved an impressive accuracy of 98.49% for CT scanning. Diallo et al. [11] used deep transfer learning to detect COVID-19 in computed tomography images. The model demonstrates training of 96.22% and testing of 93.01% accuracies respectively.

Naresh, P. V et al. [12] attempted for the identification of Covid-19, deep learning methodologies were employed such as ResNet50, VGG16, and SVM. The dataset is split 80:20 for training and testing. The 1985 training test had 496 data points. During training, the application of a 5-fold cross-validation approach was implemented.

ResNet50 achieved the best accuracy (95.16%). Avcı, I et al. [13] used the ResNet50 approach to classify the COVID-19 in X-ray pictures. The diagnosis method yielded 98.18% accuracy, 98.14% precision, 98.24% recall, and 98.19% F1-Score.

Güngör, S et al. [14] employed DenseNet201, ResNet152V2, VGG16, and Inception Resent models from deep learning to identify Covid-19. The investigations resulted in a test validation rate of 96.25% for DenseNet201. Raheem et al. [15] conducted cross-dataset analysis using CT scan and Covid CT datasets, unlike previous studies. The study employed Efficient Net, a deep learning model, and achieved the maximum accuracy of 87.68.

III. METHODLOGY

Training a convolutional neural network to classify covid is the goal of the proposed study model. processed and managed beforehand before receiving CNN architecture training. In this instance, the most effective feature extraction techniques are convolution neural networks. Kaggle provided the X-Ray scans that were used as input. The methodological flow of the suggested technique is depicted in Figure 1.

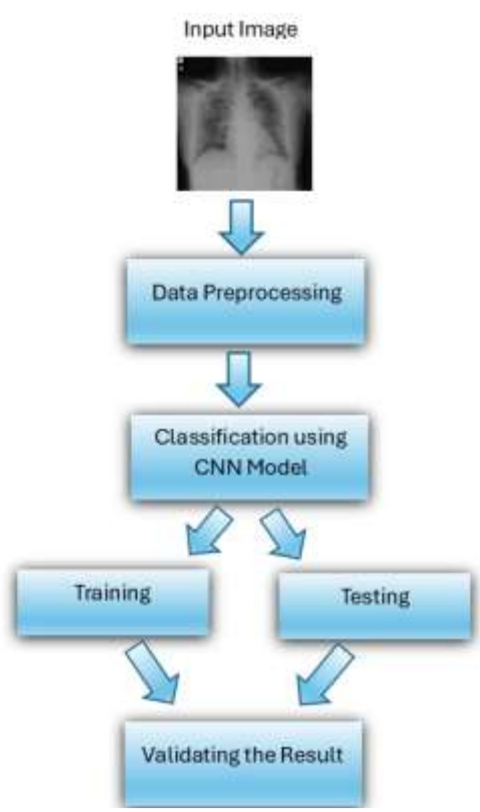

Figure 1. Proposed method flow chart.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 5| May 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402 || ISI Value: 1.188

A. *Data Set*

The first step in this inquiry is to get a publicly available dataset from Kaggle within this dataset, two categories of chest X-ray images are encompassed: Covid Positive and Covid Negative (normal). This study included 1191 photos, including 821 for training, 184 for testing, and 186 for validation. It involves the following activities: Collect chest X-ray images, preprocess them, then divide them into three halves.

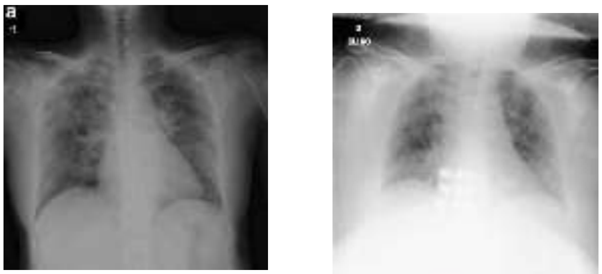

Figure 2 Images of Covid Classes

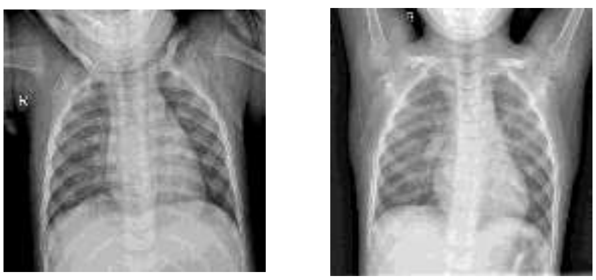

Figure 3 Images of Normal Classes

B. *Preprocessing*

Convolutional neural networks (CNNs) need all of their input pictures to be a fixed size, and in the dataset that was chosen, that size was changed to 128x128, which is the optimal size for preserving the information in the input images. In each dataset, if a fixed size There is ample variety, feature It's not required to shrink, preserving the characteristics of an input picture and improving prediction classification accuracy. A suitable size of 128x128 is chosen for resizing in this proposed approach because if the picture size is too large, it would lead to time and space complexity.

C. *CNN Model*

The CNN model design includes an attention mechanism that considers the key elements in the input images [8]. The input pictures are initially sent through a 32-filter convolutional layer with a 3x3 dimension that employs the ReLU activation function [5]. To increase stability, normalize the output from the preceding layer, and speed up training [16], batch normalization is used to this layer's output. This is followed by a dropout layer that randomly removes 25% of the neurons, a convolutional layer with 64 filters, a second convolutional layer, and a layer with a maximum pooling size of 2x2. The next layers employ convolutional layers with 128 and 256 filters [9], followed by max pooling and dropout.

The Activation function that generates attention maps for the predicted features. That maps are then multiplied with the feature maps to get the important regions of the input images. Finally, a flattened layer and fully linked layers with 512 neurons and the ReLU activation function receive the outcome of the CNN. At the end batch normalization, dropout, and

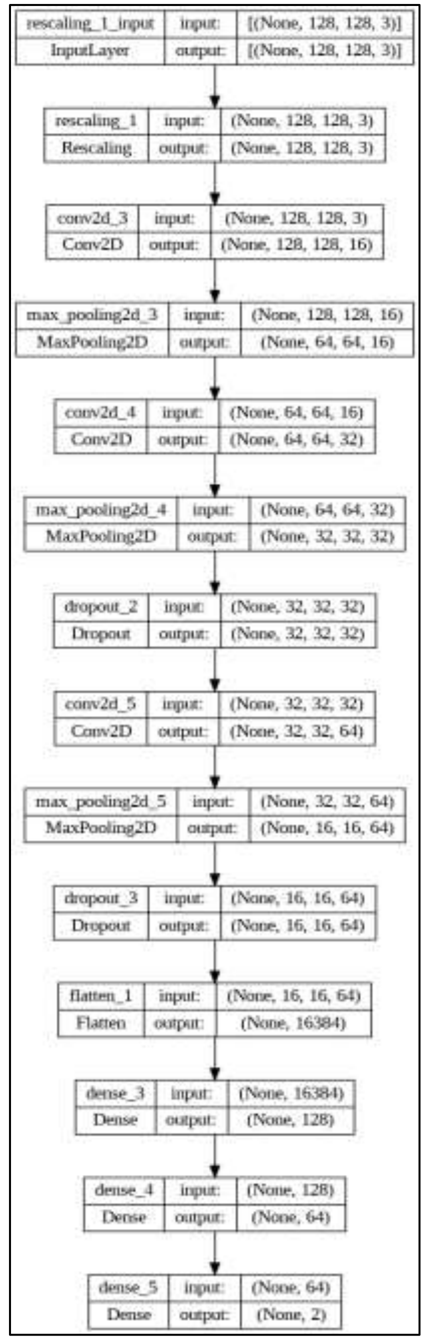

Figure 4 CNN Model Architecture

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 5| May 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402 || ISI Value: 1.188

SoftMax activation function with 2 output classes and with the top score considered as a predicted class. L2 regularization is applied to the fully connected layers to prevent overfitting.

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
rescaling_1 (Rescaling)     (None, 128, 128, 3)       0

conv2d_3 (Conv2D)           (None, 128, 128, 16)      448

max_pooling2d_3 (MaxPoolin  (None, 64, 64, 16)        0
g2D)

conv2d_4 (Conv2D)           (None, 64, 64, 32)        4640

max_pooling2d_4 (MaxPoolin  (None, 32, 32, 32)        0
g2D)

dropout_2 (Dropout)         (None, 32, 32, 32)        0

conv2d_5 (Conv2D)           (None, 32, 32, 64)        18496

max_pooling2d_5 (MaxPoolin  (None, 16, 16, 64)        0
g2D)

dropout_3 (Dropout)         (None, 16, 16, 64)        0

flatten_1 (Flatten)         (None, 16384)             0

dense_3 (Dense)             (None, 128)               2097280

dense_4 (Dense)             (None, 64)                8256

dense_5 (Dense)             (None, 2)                 130

=================================================================
Total params: 2129250 (8.12 MB)
Trainable params: 2129250 (8.12 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure 5 CNN Model Summary

This model is intended to categorize images of 2 classes Normal and Covid based on images of Chest X-ray. Multiple layers are present in the proposed CNN architecture for image classification. Convolutional layers and input layers come first, then batch normalization and max pooling. Overfitting is avoided by dropout regularization. max pooling is applied to the network after the convolutional and batch normalizations layers. The element-wise multiplication is done in a lambda layer, which is present in a final convolutional layer with a 1x1 kernel. The output is flattened and then fed through thick layers following another round of max pooling. Before the final dense layer, which comprises 2 units representing different categories, batch normalizations and dropout are performed with 21,29,250 trainable parameters.

The following layers make up the model architecture:

a. Input layer:

It accepts input pictures with a resolution of 128x128 and three RGB channels.

b. Convolutional layers:

These layers learn features from the input images using convolutional filters. There are two sets of Convolutional layers with 32 and 64 filters respectively[1], followed by Batch Normalization to normalize the convolutional layer and a ReLU activation function, a Max Pooling layer with a pool size of 2x2 is employed to diminish the dimensionality of the output feature maps [2]. Additionally, to mitigate overfitting, a Dropout layer with the rate of 0.25 is incorporated.

c. Set of Convolutional layers:

A Max Pooling layer is introduced with a pool size of 2x2, Batch Normalization, ReLU activation function[7], and a convolutional layer with 128 and 256 filter respectively are used. Once more to mitigate overfitting, a Dropout layer is introduced with a rate of 0.25.

d. Fully Connected Layer:

Two Dense layers are then added after . The first dense layer consists of 512 units and used L2 regularization with a 0.001 penalty and a ReLU activation function. to avoid overfitting, To enhance training stability and further mitigate overfitting, Batch Normalization is introduced along with a Dropout layer featuring a rate of 0.5. To anticipate the probability distribution between 2 classes a SoftMax activation function is introduced to the final 2 class dense layer.

e. Output

The final layer is the dense layer to anticipated probability distribution of 2 classes

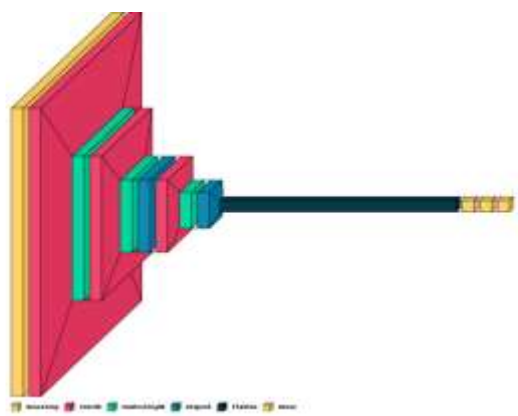

Figure 6 CNN Model Architecture 3D Plot

IV. RESULT

We evaluate the efficacy of our approach using the matrix presented in Figure 7 and 8. The variables consist of False Positives (FP), True Negatives (TN), True Positives (TP), and False Negatives (FN). The term "TP" indicates that the patient has diabetes, as determined by the models. FP indicates that the patient does not have covid, but the models incorrectly identified it as such. Patients with normal cases are referred to as TN, whereas models are categorized as Normal. According to FN, the patient had Covid, but the models wrongly recognized them as not having it.

The classifier's dependability defines the fraction of right positive items among genuine. Recall is the proportion of

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 5| May 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402 || ISI Value: 1.188

properly identified circumstances compared to the overall count of anticipated situations, While accuracy is the percentage of precisely classified instances compared to the total number of occurrences. The F1-score is calculated by taking the harmonic average of accuracy and recall. A model with a score closer to 1 is considered more effective. The following formulas are used to calculate all metrics [14].

- Accuracy A = (TP+TN)/ (TP+FN+FP+TN)
- Precision P = TP/ (TP+FP)
- Recall R = TP/ (TP+FN)
- F1-score F1 = 2P∗R/ (P+R)

Figure 7 Training data classification report.

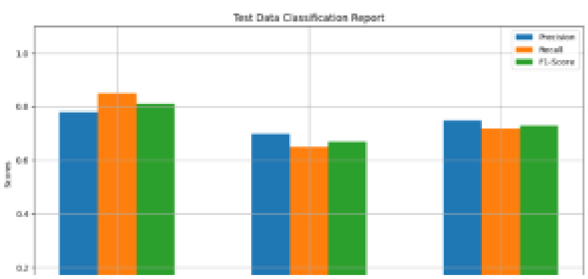

Figure 8 Testing data classification report.

Figure 6 and 7 classification reports for both the training and test data shows robust model performance, with high precision and recall scores. In the training set the model demonstrates exceptional accuracy achieving 98.53% it effectively distinguishes between the two classes with a precision of 96% for class 0 and 100% for class 1 albeit with a slightly lower recall for class 1 at 88%. Similarly on the test set the model maintains its high accuracy at 99.17% showcasing its generalization capability. Although there's a slight decrease in recall for class 1 compared to the training set, it remains at a commendable 89%. Overall, the model exhibits consistent and reliable performance, demonstrating its effectiveness in classifying instances accurately and efficiently.

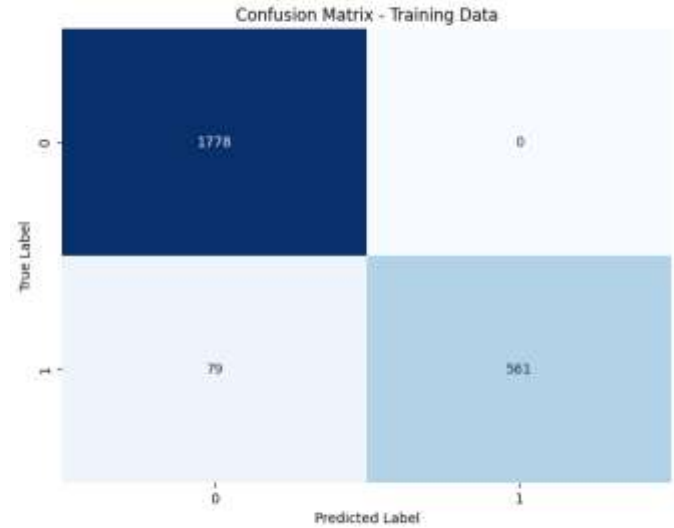

Figure 9 depicts the Confusion Matrix of the Training data.

Figure 10 illustrates the Confusion Matrix of the Test data.

Figure 8 and 9 represent the confusion matrices illustrate the model classification performance on both the training and test datasets. Within the training set, The representation is correct identifies 1778 instances of class 0 and 561 instances of class 1.it misclassifies 79 instance of class 0 and 17 instances of class 1. Similarly on the test set the model accurately predicts 445 instances of class 0 and 143 instances of class 1 while misclassifying 17 instances of class 1. These matrices provide a clear visual representation of the model's ability to correctly classify instances as well as its tendency for misclassification thereby offering valuable insights into its performance characteristics.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 5| May 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402 || ISI Value: 1.188

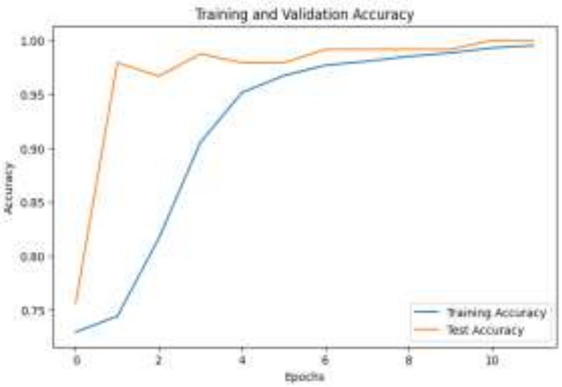

Figure 11 CNN model training and validation accuracy.

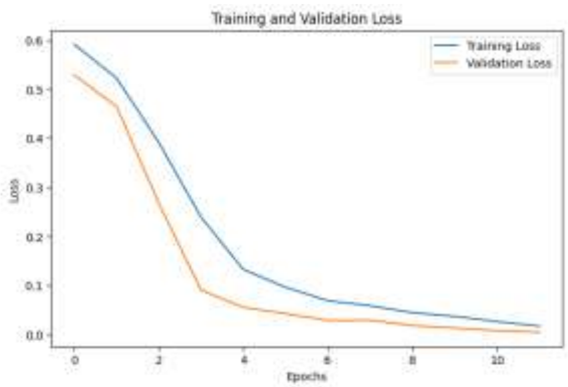

Figure 12 CNN model training and validation accuracy.

The Convolutional Neural Network model achieves remarkable performance with a training loss of 0.0444 and accuracy of 98.53%. In validation it demonstrates even higher proficiency attaining a loss of 0.0181 and accuracy of 99.17%. These results underscore the effectiveness of the CNN architecture in accurately classifying data particularly in distinguishing between different classes with high precision.

Tabel I. Accuracy report of training and testing.

	Class	Precision	Recall	F1-Score
Training	Normal	0.96	1.00	0.98
	Covid	1.00	0.88	0.93
Testing	Normal	0.96	1.00	0.98
	Covid	1.00	0.89	0.94

Tabel 1 represent the training and testing stages, the CNN model scores between 0.96 and 1.00, indicating great accuracy for both normal and COVID situations. The recall shows a modest drop, especially in testing, indicating that some COVID instances were missed, even if accuracy for COVID cases is flawless. Even so, the total performance is still good, suggesting that the CNN model can effectively detect COVID.

V. CONCLUSION

The present study uses a deep learning strategy to distinguish between covid-19 afflicted and unaffected individuals in mammography X-ray pictures. We propose deep model comparisons to determine which models perform better in illness categorization. Deep models demonstrated higher accuracy and lower loss rates during training and validation for covid-19 illness detection. Our findings show that deep learning-based CNNs can accurately and efficiently recognize and diagnose covid-19 disease. Modality processing leads to significant improvements in accuracy measures.

REFERENCES

1. *Pereira, R. M., et al. (2020). "Identifying COVID-19 in Chest X-rays with Different Methods."*
2. *Burmese, L., et al. (2020). "Using Explainable Deep Learning to Detect Lung Diseases and COVID-19 in X-rays."*
3. *Panwar, H., et al. (2020). "Quick COVID-19 Detection in X-rays Using Deep Learning."*
4. *Tung-Chen, Y., et al. (2020). "Comparing Chest CT Scans and Lung Ultrasounds for COVID-19."*
5. *Khan, A. I., et al. (2020). "Introducing a Deep Neural Network for COVID-19 Detection in Chest X-rays."*
6. *Soares, E., et al. (2020). "Releasing a Dataset of Real Patient CT Scans for Identifying SARS-CoV-2."*
7. *Cifci, M. A. (2020). "Proposing a Deep Learning Model for Diagnosing Coronavirus Disease from CT Scans."*
8. *Meepaganithage, A., & Fernando, M. (2022). "Detecting COVID-19 Pneumonia in Chest X-rays Using Deep Learning Techniques."*
9. *Nefoussi, S., et al. (2021). "Comparing Deep Learning Networks for Recognizing COVID-19 in Chest X-ray Images."*
10. *Kumar, S. P., et al. (2023). "Comparing Deep Learning Methods for COVID-19 Detection."*
11. *Diallo, P. A. K. K., & Ju, Y. (2020). "Accurate COVID-19 Detection with Deep Learning and X-ray Images."*
12. *Naresh, P. V., et al. (2023). "Classifying COVID-19 from Medical Images with Deep Learning."*
13. *Avcı, İ., & Alzabaq, A. (2022). "Using AI to Detect COVID-19 from X-ray Images: Research and Future Directions."*
14. *Güngör, S., & Kaya, M. (2021). "Automatically Detecting COVID-19 from CT Images with Deep Learning."*
15. *Raheem, A. K. A., et al. (2023). "COVID-19 Detection with Inception v3 Deep Learning Algorithm."*
16. *Chen, W., et al. (2020"Using Chest X-ray Images to Diagnose COVID-19": A Comparative Study."*
17. *Li, S., et al. (2021). "Deep Learning Approaches for COVID-19 Detection from Chest X-rays: A Review."*
18. *Wang, Z., et al. (2022). "Enhancing COVID-19 Diagnosis with Multi-Modal Imaging and Deep Learning."*
19. *Patel, R., et al. (2023). "Investigating the Role of AI in COVID-19 Diagnosis and Prognosis from Medical Images."*

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 10| Issue: 5| May 2024|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2024: 8.402 || ISI Value: 1.188

20. *Zhang, H., et al. (2023). "Addressing Challenges in COVID-19 Detection Utilizing Deep Learning Techniques on Chest X-rays."*