International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Light Weight Grid Search Based Ensemble Model for Covid-19 Classification in Chest X-Rays

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Submitted: 23/04/2023 **Revised**: 24/06/2023 **Accepted**: 04/07/2023

Abstract: COVID-19, a highly infectious disease caused by a severe acute respiratory syndrome, poses a significant threat as it can lead to fatalities within a matter of days. The current pandemic necessitates extensive testing, which is a laborious and time-consuming process. Recent advancements done in Deep Learning, particularly in the field of image analysis, have proven to be effective. This study proposes and investigates the performance of three Convolution Neural Networks (CNNs) utilizing transfer learning and compares them against other existing architectures. To conduct the experiments, a publicly available dataset consisting of 3,792 Chest X-Rays categorized into three categories was employed: COVID'19 patients (labeled as Covid), patients with a negative diagnosis (labeled as Normal), and those with pneumonia. The chosen architectures for evaluation were vgg16, resnet50, and a custom CNN. Additionally, ensemble models were constructed and tested using various combinations. The findings demonstrated that the ensemble models consistently yielded the most favorable outcomes. Furthermore, all three CNN architectures exhibited remarkable performance, achieving an average accuracy of 97.7%.

Keywords*: *Covid-19, VGG16, ResNet50, CNN, Chest X-Rays, Ensemble.

1 Introduction

COVID-19, a respiratory illness caused by the novel coronavirus known as severe acute respiratory syndrome (SARS-CoV-2), first emerged in the city of Wuhan, China [1]. On January 30, 2020, the World Health Organization (WHO) confirmed COVID"19 a global public health emergency [2]. To enable early detection, real-time reverse transcription polymerase chain reaction (RT-PCR) has been extensively utilized [3-5] have suggested that the sensitivity of the RT-PCR test may be limited, leading to false-negative results even in individuals who are infected. This poses a risk as these individuals could unknowingly spread the virus to others or develop severe symptoms without appropriate isolation. Additionally, the time-consuming nature of this test delays the rapid identification and tracking of positive COVID-19 cases, which is crucial [6].

In recent years, the advent of artificial intelligence has prompted researchers to utilize deep learning architectures for the detection of COVID-19 using chest X-rays.

Deep learning, a subset of machine learning inspired by the workings of neurons in the human brain, has witnessed remarkable advancements [7, 8]. Its built-in ability to learn independently and generate unprecedentedly efficient solutions has contributed to its widespread adoption [9]. Consequently, deep learning finds applications across diverse industries and academic domains. Unlike traditional machine learning, deep learning has the capability to extract image features, thus reducing processing time automatically. Leveraging deep learning for COVID-19 detection yields higher accuracy within significantly shorter timeframes [10, 11].

Ensemble modeling involves the creation of multiple diverse models to make predictions. The ensemble model combines the predictions of each base model, resulting in a final prediction for new, unseen data. Leveraging ensemble models can enhance the overall analytical performance by taking the predictive abilities of two or more base "learner" models. This approach mitigates bias and variance in the base learners, leading to a more robust and accurate model.

In this research paper, we introduce the Ensemble Deep Learning Model as a highly effective screening approach for the identification of COVID. Our proposed architecture achieves superior accuracy by analyzing Chest X-rays and examining visual markers present in the chest radiography imaging of COVID-19 patients. Notably, our model demonstrates remarkable performance with a concise number of layers and optimized parameters, thereby reducing computational time and hardware costs. Comparative analysis with other models highlights the promising outcomes achieved by our proposed model.

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Major contributions of this work are:

1 The Proposed Ensemble Model combining VGG16, ResNet50 and Custom CNN is developed to accurately classify Covid'19, Viral Pneumonia and Normal in Chest X-Ray Scans.
2 The Integration of VGG16, ResNet50, and Custom CNN yielded an accuracy of 97.0 % which was highest among the tested Combinations.'
3 Best Hyperparameters obtained from Grid Search method were tested on the model.
4 The developed ensemble model performs in classifying Covid19 from Chest X-Rays.

The remaining of the study is as follows : Section 2 Presents related works, Section 3 details the proposed methodology, Section.4 Experimental Analysis Section 5 Discussions

2. Related Works

Since the Covid-19 pandemic, substantial efforts have been dedicated to the efficient detection of Coronavirus by medical experts, researchers, and scientists. Research has prominently employed deep learning techniques to enable rapid virus detection using Chest X-rays. Extensive investigations have been initiated to search for these approaches.

In 2022, Musallam-et.al. introduced DeepChest, a convolutional neural network, utilizing 7512 chest X-Rays images. Results demonstrated an accuracy of 96.5% for COVID19, general pneumonia, and normal categories [12].

In their study, Das et al. proposed using CNN models, namely DenseNet201 model Resnet50V2, and InceptionV3, for their proposed work [13]. These models were trained Singly to make independent predictions. By employing the weighted average ensemble technique, they successfully combined the models and achieved a remarkable classification accuracy of 91.62%. Additionally, the researchers designed a user-friendly graphical user interface (GUI) specifically tailored for doctors, which will prove valuable in detecting COVID patients.

Apostolopoulos and Mpesiana [14] conducted a study on the identification of COVID'19 using state of art models applied to chest X-ray (CXR) scans. The dataset was separated into two classes: (i) bacteria pneumonia and (ii) viral pneumonia, allowing for comprehensive model evaluation. To facilitate optimal feature extraction, the images underwent rescaling. 1428 X-rays's images were analyzed, comprising 224 COVID'19 cases, 700 instances of common bacterial pneumonia, and 504 normal conditions. The models were checked based on two classification accuracy: (i) multi labels (3) (COVID19, pneumonia, and normal) and (ii) binary labels (COVID19 and normal). VGG-19 model and MobileNetV2 outperformed other classification models, achieving an impressive correctness of 98.75% for the binary classifier and 97.40% for the multi classifier. Ashoure et al. [15] employed an ensemble bag of features to classify COVID19 in X-ray images. While non-ensemble methods have yielded promising results for a newly emerged and relatively unfamiliar disease, researchers have recognized the potential for improved outcomes by using combined techniques known as ensemble models. This approach has proven successful in various medical and biomedical domains. In a related study,

In their work, Song et al. [16] introduced an ensemble model consisting of a pre-processing stage and a DRENet. The pre-processing step involved scaling the image, generating sub-images containing relevant areas, and extracting relational features. The DRENet was constructed using three parallel ResNet 50 models, each receiving the output from the pre-processing stage. The results from each ResNet were combined using an MLP Net. The ensemble model achieved impressive accuracy of 93%.

3. Proposed Methodology

The objective of the proposed model is to construct a highly effective ensemble model for COVID-19 prediction. To achieve this, three deep learning models, namely VGG16 model, ResNet50 model, and Custom CNN, are fine-tuned using the Grid Search technique to identify the optimal parameters.

This fine-tuning process enhances the performance of each model, while parallel processing is employed to minimize computations within the fully connected neural network. The combination of these strategies contributes to the new development of an efficient ensemble model for precise COVID-19 prediction.

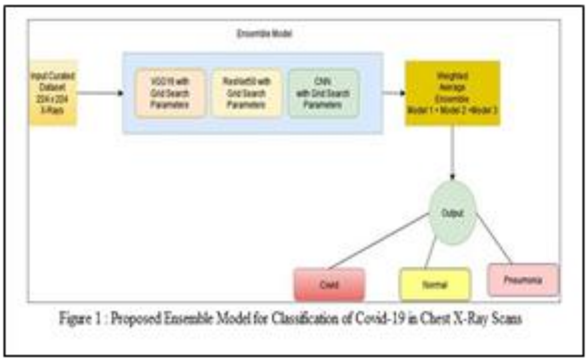

Fig. 1. Proposed Ensemble Model for Classification of Covid-19 in Chest X-Ray Scans

3.1 Description of Dataset

Several datasets contains X-Ray's images of normal individuals and cases of pneumonia infection have been identified. However, readily available datasets, specifically consisting of X-ray images of COVID-19-infected patients are limited. To gather a dataset of covid19-infected X-Rays , various sources such as Github repo were utilized. The dataset was obtained from the kaggle database

Fig. 2 showcases few images from these three categories. The dataset comprises a total of 3,792 X-ray images, with 1,097 COVID-19-infected cases, 1,345 pneumonia cases, and 1,350 normal cases. For training and testing purposes, 80% of the images were allocated as the training, while the remaining 20% constituted the testing. Thus, 3,036 X-ray images were used for training, while 756 were reserved for testing.

A detailed breakdown of the dataset size and partition can be found in Table 1.

Table 1. Class Distribution of Dataset

	Covid	***Normal***	***Pneumonia***	***Total***
Train	877	1083	1076	3036
Test	220	267	269	756
Total	1097	1350	1345	3792

3.2 DATA PREPROCESSING

Deep learning models typically require input images to have the similar size. However, the samples in our dataset vary in size and shape. Initially, our CXR images dataset contained samples of different sizes, ranging from 150 × 150 to 600 × 600.

To address this issue, we standardized the image sizes. Given the heterogeneous nature of the CXR images in the dataset, we transformed all images to a consistent size of 224 × 224, ensuring uniformity for subsequent deep learning model training and analysis.

3.3 Ensemble Model

Ensembling is a technique employed in deep learning to address the high-variance problem of neural networks [17]. Ensembling enhances the overall results by training multiple models and combining their predictions. Recent research has shown that ensemble methods provide more remarkable accuracy by introducing some bias to balance the variance caused by relying solely on a single neural network trained on the same dataset [18].

Various algorithms can be utilized to combine classifiers, which effectively reduces overfitting and generates a smoother regression model. Averaging, in particular, is an ensemble method that leverages the strengths of multiple models to achieve more accurate predictions.

Each classifier contributes its predictions, and the target class is determined based on the maximum average prediction. Despite its simplicity, averaging has been suggested as the optimal technique. For instance, let's consider three different models, M1, M2, and M3, each providing individual predictions.

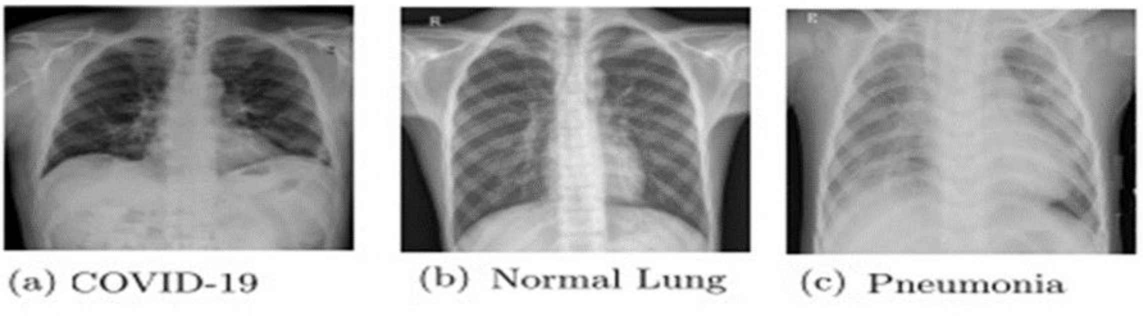

Fig 2. Samples of Dataset Contains (a) Covid, (b) Normal, (c) Pneumonia

Table 2. Working Principal of Average Ensemble

Classes	Prediction Probability for Model : 1	Prediction Probability for Model : 2	Prediction Probability for Model : 3	Average
0	0.97	0.85	0.92	0.91
1	0.75	0.64	0.81	0.73
2	0.55	0.75	0.92	0.74

In this example, for Class 0, we got an average of 0.91 as our target prediction. Class "0" denotes Covid, Class 1 denotes Normal, and Class 2 denotes Pneumonia

3.3.1 Loss Function

Given that our dataset consists of multiple classes, we have employed categorical Cross-Entropy as the loss function in our approach. Cross-Entropy quantifies the discrepancy between two probability distributions, and thus, the cross-entropy loss is determined by the disparity between the predicted probability and the true label. The equation for the loss function is presented below as equation (1).

$$L(y - \hat{y}) = -\sum_{i=1}^{n} y_1 \log \hat{y_i} \quad (1)$$

3.3.2 Optimizer

In order to perform optimization to our deep learning models, we have employed the Adam optimizer, which can be understood as a blend of RMSProp and Stochastic Gradient Descent with Momentum. It incorporates a moving an average of the gradient instead of directly using the gradient itself. The operational mechanism of the Adam

optimizer is represented by the formula presented below as equation. 2.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$\boldsymbol{v_t} = \beta_1 v_{t-1} + (1 - \beta_2) g_t^2 \quad (2)$$

3.3.3 Classifier

For classifying the obtained feature vector, we utilize the softmax function in conjunction with a multiple layer perceptron network. The softmax function is applied to a vector of logits, which are the outputs of the last fully connected layer of the CNN. This function transforms the logits to relative probabilities, enabling the sorting of required classes in multi class classification. The softmax equation is described below. Eq. (3)

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

σ= softmax

$\vec{z}$= input vector

e^{z_i} = standard exponetial function for input Vector

K= number of classes in the multi-class classifier

e^{z_j}= standard exponential function for output vector

3.4 Grid Search Hyper Parameters

The GridSearchCV, which facilitates a grid search, exhaustively evaluates and identifies the best parameters from a predefined grid of parameter values specified in param_grid. We have employed the grid search approach on individual models and ensembled them to improve accuracy. By systematically exploring various parameter combinations, grid search enables us to optimize the models' performance and enhance the overall accuracy of the ensemble.

3.5 Metrics for Evaluation

Accuracy: It measures the amount of correctly predicted instances out of the total number of instances in a dataset.

Accuracy = $\frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}}$

Precision: It measures the amount of correctly predicted positive instances (true positives) out of all instances predicted as positive (true positives + false positives)

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

Recall: Recall quantifies the model's ability to correctly identify positive instances from the total number of positive cases present in the dataset

Recall = $\frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}}$

F1Score: The F1 score considers both precision (the ability of the model to make accurate positive predictions) and recall (the ability of the model to identify all positive instances correctly). It is calculated using the formula:

F-1 Score = $\frac{\boldsymbol{2\ x\ Precision * Recall}}{\boldsymbol{Precision+Recall}}$

Additionally, the model exhibits a significantly low loss, indicating a minimal rate of incorrect predictions. Loss plays a fundamental role in deep learning neural networks as it quantifies the error in our model's predictions.

	precision	recall	f1-score	support
covid19	0.95	1.00	0.97	18
normal	0.95	1.00	0.97	19
pneumonia	1.00	0.93	0.96	27
accuracy			0.97	64
macro avg	0.97	0.98	0.97	64
weighted avg	0.97	0.97	0.97	64

Fig 3.Classification Report

The loss is determined using a loss function, which serves as a method to compute the magnitude of the error. In this case, we have employed categorical cross-entropy as the chosen loss function for our model. Categorical cross-entropy effectively measures the discrepancy between predicted and actual class probabilities, enabling accurate assessment and optimization of the model's performance.

4. Experimental Analysis

The models are trained using the Adam Optimizer. The training data is processed in batches of size 32, and the training process lasts for 25 epochs. The epoch number is determined through the Model Checkpoint and Early Stopping techniques. The performance of the developed model is measured with metrics such as accuracy, precision, recall F1-score and ROC curve. In the case of the multiclass classifier, the training, testing are recorded as 10,842.1 seconds and 127.0 seconds, respectively.

4.1 Experimental Setup

Google colab is used which provides 12GB of RAM and NVIDIA Tesla K80 GPU for 8 Hours along with tensforlow and keras libraries.

4.2 Analysis of Results

Fig 3 shows the the classification report for the multiclass classficiation. We have received average accuracy of

0.97% with our model. The other details like precicion, recall and F1 Score are described below.

1. Read X-Ray Images
2. Output : Covid-19 Classification(Covid,Normal,Pneumonia)
3. Begin
4. Image <- Read Chest X-Ray Images
5 Image <- Resize the Image(224x224)
6. $Image_{train}$, $Image_{Test}$ --- Split
7. for(model I = 1 to 3)
8. Model 1 --- load the model
9. Apply Grid Search for best parameters for model1
10. Model - Train (Test Image)
11. Model 2- load the model
12. Apply Grid Search for best parameters for model 2
13. Model - Train (Test Images)
14. Model 3 - Load the model
15. Apply Grid Search for best parameters for model 3
16.Model -Train (Test Images)
17. Model Save.
18. Load and append all three models
19. Apply Average Ensemble model
20. Evaluate the Model
21. Print Results
22. End

Algorithm 1. Steps for covid 19 detection using Average Ensemble model

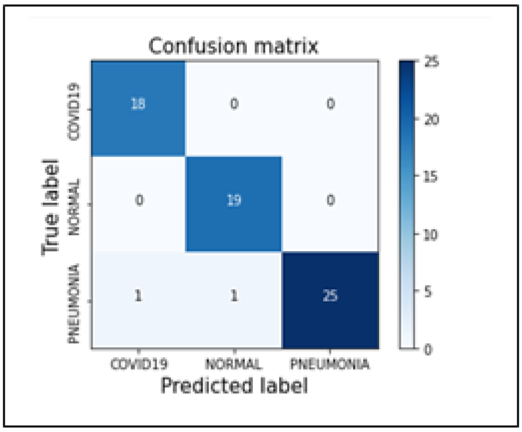

Fig 4. Confusion Matrix

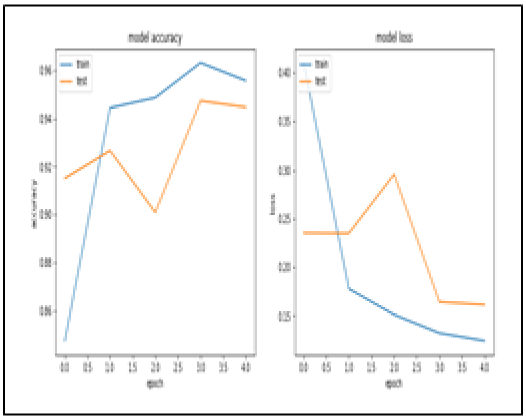

Fig 5: Epoch vs accuracy and Epoch vs loss

5. Discussion

The comparision with other models are described in Table 3 Based on the results our model has outpeformed with other models which is described in the comparision table The important factor of the system is that the model has developed with ensemble learning technique with best parameters to reduce the computational time and no of layers compared to recent research. future research will be performed to improve the model to detect all kinds of lung diseases.

6. Conclusion

Covid has caused immense loss of life and inflicted tremendous suffering upon families worldwide. In an effort to combat this crisis, we have developed a model capable of automatically detecting COVID19 from CXR images.

Study	Architecture	Accuracy
Ozturk et al.[19]	DarkNet	87.02%
Sethy et al.[20]	ResNet50+SVM	95.4
Khan et al [21]	CoroNet (Xception)	94.52
Singh et al [22]	MODE-based CNN	93.3%
Hemdan- et al [23]	COVIDx-Net	90.0%
Wang et al.[24]	COVID-Net	92.40%
C. Ouchicha et al. [25]	CvdNet	96.69%
Elzeki et al.[26]	CXRVN	93.07%
Toraman et al [27]	CapsNet	84.22%
Kumar et al [28]	ResNet50 + SVM	95.38%
Rahimzadeh & Attar, [29]	Xception and ResNet50V2	95.5%
Our proposed Model	**VGG16 +ResNet50+ CNN (Ensemble)**	**97.00%**

Table 3. Comparision Table

Our proposed model leverages deep learning techniques to extract distinctive and high-level features from these CXR, accurately classifying them into COVID19, pneumonia, and normal categories. Our results showcase impressive performance with 97.00% accuracy future enhancements, enabling the detection of not only COVID-19 but also other lung diseases.

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