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An Adaptive Grid Search Based Efficient Ensemble Model for Covid-19 Classification in Chest X-Ray Scans

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ABSTRACT- Covid has resulted in millions of deaths worldwide, making it crucial to develop fast and safe diagnostic methods to control its spread. Chest X-Ray imaging can diagnose pulmonary diseases, including Covid. Most research studies have developed single convolution neural network models ignoring the advantage of combining different models. An ensemble model has higher predictive accuracy and reduces the generalization error of prediction. We employed an ensemble of Multi Deep Neural Networks models for Covid.19 classification in chest X-Ray scans using Multiclass classification (Covid, Pneumonia, and Normal). We improved the accuracy by identifying the best parameters using the sklean Grid search technique and implementing it with the Optimized Weight Average Ensemble Model, which allows multiple models to predict. Our ensemble model has achieved 95.26% accuracy in classifying the X-Ray images; it demonstrates potential in ensemble models for diagnosis using Radiography images.

General Terms: Image Classification, Deep Learning, Neural Networks, Chest X -Rays

Keywords: Covid-19, VGG-16, ResNet50, InceptionV3, Ensemble,

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1. INTRODUCTION

Since December 2019, the Covid Virus, commonly known as the Coronavirus, has spread globally after originating in Wuhan, China [1]. Early detection is critical in minimizing the spread of the virus, requiring prompt isolation of infected individuals. Current screening techniques for COVID-19 include gene sequencing, blood specimens, and RT-PCR; although it has limitations in accuracy [2,3]. The standard method for diagnosing the disease is RT.PCR. It is used to perceive the occurrence of antibodies against the virus, and molecule testing of respiratory sample is recommended for diagnose and confirm the virus contagion in the laboratory. However, this process is time-consuming and can produce false-negative results. Moreover, many developing countries cannot conduct large scale covid tests due to their increasing cost, which makes immediate diagnosis based on symptoms crucial. Treatment for COVID-19 patients is challenging, as there is currently no cure, and patients often require hours of waiting time [4]. To address these challenges, chest imaging has emerged as an alternative to RT-PCR, and a small dataset of X-Ray images related to COVID-19 has become helpful for training machine learning (ML) algorithms to detect the virus automatically [5,6]. With the increase in Computer Diagnostic Systems using artificial intelligence systems detecting the presence or absence of diseases has become faster and more efficient. Deep learning algorithms, specifically Convolution Neural Networks (CNNs), have shown promise in processing and analyzing medical images [7]. Studying new classification algorithms using deep learning architectures can help healthcare experts and researchers' persons. Ensemble learning, which combines CNN's features, can produce additional accurate metrics such as accurateness, recall, and F1 Score. Collaborative systems have confirmed high efficiency and usefulness across numerous challenging domains [8]. Recently many studies have developed different models to predict the disease which are depended upon single network these models have limitations in predicting accuracy causing generalized errors. Recent studies have shown that ensemble models have high predicting accuracy which is combination of many base models more reliable to produce better results. In this study, we propose using an ensemble technique, which combines multiple models (VGG16-ResNet50, InceptionV3), to get better correctness, precision, recall, and F1 score metrics for virus detection using CNNs. We have tested different CNN Architectures and combined the top three to create one ensemble model using a fully connected neural network. Ensemble systems have been successful in various problem

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domains, and their use in machine learning has gained attention from the research community. Our proposed approach can help medical professionals in remote areas where specialist radiologists cannot provide faster treatment for patients with COVID-19.

Author's contribution in this research is as follows.

1. The authors used Pre-trained Deep Network learning models for multiclass classification with an Optimized Weight Average Ensemble Model (OWAE) for the classification of disease in Chest X-Rays
2. The authors implemented extended-based Transfer learning models to combine the base classifiers.
3. The Grid search-based algorithm was used to assign the best parameters.

In this paper, we explain a detailed analysis of our proposed approach for classification. *Section 2* describes the related works and *section 3* clarifies the dataset, Data Pre-Processing, and model techniques. *Section 4* explains the performance evaluation, evaluation parameters, experimental setup, and results of the model; in *Section 5*, we conclude our study and discuss the research.

2. RELATED WORKS

This section explores the research work and the analysis approach of detecting the Covid-19 which is done by various authors are explained. According to [9] Ozturk *et al.* (2020) discuss thatVGG-16 was employed on chest X-rays to identify COVID-19. The researchers examined 5,941 chest X-ray scans from 2,839 individuals, including 3,616 normal, 1,219 pneumonia, and 1,106 COVID-19 instances. The authors reported a total correctness of 98.08%, a compassion of 99.24%, and a specificity of 95.14% [10]. VGG-16 was utilized to analyze COVID-19 on chest X-rays in this investigation. The researchers analyzed 2,610 chest X-ray scans from 708 patients, comprising 1,170 normal, 800 pneumonia, and 640 COVID-19 instances. The authors reported a correctness of 97.95%, sympathy of 98.6%, and specificity of 97.59% [11]. In this work, Inception v3 was utilised to notice COVID-19 in chest X-rays. The researchers analysed 1,025 chest X-ray scans from 250 patients, including 700 normal, 100 pneumonia, and 175 COVID-19 instances. The authors reported an overall accuracy of 98.3%, sensitivity of 98.3%, and specificity of 98.3% [9]. In this work, Inception v3 was utilized to detect COVID-19 in chest X-rays. The researchers analyzed 866 chest X-ray images from 234 patients, including 224 normal, 337 pneumonia, and 305 COVID-19 instances. The authors reported an accuracy of 97.3%, sensitivity of 98.4%, and specificity of 96.0% [12]. According to Singh *et al.* (2021) ResNet50 was utilized to identify COVID-19 on chest X-rays in this investigation. The researchers analyzed 2,765 chest X-ray scans from 807 patients, comprising 1,048 normal, 792 pneumonia, and 925 COVID-19 instances. The authors reported general exactness of 94.2%, sensitivity of 96.5%, and specificity of 91.6% [13]. ResNet50 was utilized to diagnose COVID-19 on chest X-rays in this investigation. The researchers used a dataset of 19,684 chest X-ray pictures from 5,865 individuals, including 15,354 normal, 2,266 pneumonia, and 1,064 COVID-19 cases. The authors reported an overall accuracy of 93.5%, sensitivity of 91.8%, and specificity of 94.8% [14]. ResNet50 was utilized to identify COVID-19 on chest X-rays in this investigation. The researchers analyzed 6,500 chest X-ray scans from 2,943 patients, including 4,192 normal, 1,003 pneumonia, and 1,305 COVID-19 instances. The authors reported an overall correctness of 98.08%, sensitivity of 98.14%, and specificity of 98.03% [15]. In this study, an ensemble model incorporating Vgg-16, Inception v3, and ResNet50 was employed to diagnose virus in chest X-rays. The researchers used a collection of 16,756 chest X-ray pictures from 4,356 individuals, including 7,663 normal, 4,295 pneumonia, and 4,798 COVID-19 cases. The authors reported an overall correctness of98.5%, sensitivity of 98.2%, and specificity of 98.8%.[16]

3. MATERIALS AND METHODS

Methodology is discussed in 3.3, 3.4, 3.5, and 3.6.

3.1 Dataset narrative

The customized Dataset of Chest Radiography Images (X-Rays) contains three classes that are filtered and combined to make it final.

The *dataset was taken from Kaggle and GitHub*, and the image types were filtered. The dataset contains Covid, Normal, and Pneumonia Cases Chest X-Rays Images. A brief information about the dataset is given in table1:

Table 1: Covid Dataset: Class Distribution in training and testing to evaluate the proposed Model.

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

3.2 Data Pre-Processing

In the context of deep learning model, the model requires the input Image to be of a fixed size, but the CXR images in our dataset have different sizes and shapes. Initially, the CXR images in our dataset varied in size, with dimensions ranging from 400×300. To ensure consistency and facilitate processing, we resized all CXR samples in the dataset to a standard size of 224 x 224. The total number of samples used in the dataset is 3792.

3.3 Transfer Learning Technique

Training state-of-the-art deep convolution models requires many parameters and large datasets. However, more large datasets are unavailable for analyzing medical images due to privacy concerns. As a result, researchers have been using transfer learning techniques to train their models on smaller datasets. Many pre-trained models have been made available for reuse by different research groups [17, 18], with most being already trained on the ImageNet dataset [19]. This study used the pre-trained models VGG16, InceptionV3, and ResNet50 for multiclass classification. We removed the fully connected layers from the State-Of-Art models to decrease the

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number of layers and added dense layers with fewer filters. We also froze the weights of these models and only trained the newly added layers for the ending consequences.

3.4 Improved Weighted Average Ensemble Technique

Although research has shown that ensemble models can outperform a single model [20], many studies still rely on individual models for classification results. However, research experts often use collaborative models to improve consequences because a single model may only extract some relevant features from a dataset. This study utilized an optimized biased regular ensemble technique for multi-classification. The average ensemble method is weighted equally for generating predictions by assigning weights to each model based on its contribution. To determine the optimal weights, a grid search technique was employed.

3.5 Grid Search Optimization

The 'GridSearchCV' function in sklearn [21] enables the grid search-based algorithm to classify the optimal hyper parameters. Although there have been many suggested hyper parameter optimization methods and years of scientific research into global optimization, grid search remains state-of-the-art due to its easy implementation and ability to find much better solutions than manual sequential optimization. It also offers better reliability and is suitable for low-dimensionality problems.

3.6 Model Architecture

In this study, the CNN model comprises two blocks: the feature extraction, fully connected block. To leverage the learned features from pre-trained CNN models, we employ the feature extraction blocks of VGG-16, InceptionV3, and ResNet50 for classification. We removed last layers and subsequently added global average pooling (GAP), Flatten, and dense layer and dropout layers after the feature extraction block. Specifically, we add a single dense layer with 512 neurons and a dropout rate of 20%. This dropout layer acts as a regularize and prevent over fitting of the model. We freeze the masses of the feature extraction stages and only train the left-over layers on the Chest X-Ray dataset. Finally, we use the dense layer along with a *softmax* function and save the models then perform summation of models and perform averaging using *np.argmax*

4. Performance Evaluation

Section 4.1 details various evaluation metrics and their formulations, whereas Section 4.2 outlines the new setup. In Section 4.3, the results of three class multi classification analysis are presented and discussed.

4.1 Evaluation Parameters

To assess the organization presentation of deep convolution neural network models, a confusion matrix can be used to present the factual and foretold labels in a tabular format. Since the confusion matrix, parameters such as sensitivity and recall, precision, F1-score, and accuracy container be calculated. The corresponding formulations for computing these parameters are provided below.

TP: the model predicts the true class as true.
TN: the model predicts the false class as false
FP: the model wrongly predicts the true class.
FN: the model wrongly predicts the false class.

Accuracy: the proportion of the quantity of precise predictions complete by the model to the total amount of predictions made.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

Precision: defined as the ratio of true positive predictions to all of the model positive predictions.

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (2)$$

Recall: it is defined as the proportion of true positive predictions to the total number of actual positive samples.

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (3)$$

F1-score: it is a harmonic mean of precision and recall.

$$\text{F-1 Score} = \frac{2\ x\ Precision * Recall}{Precision+Recall} \qquad (4)$$

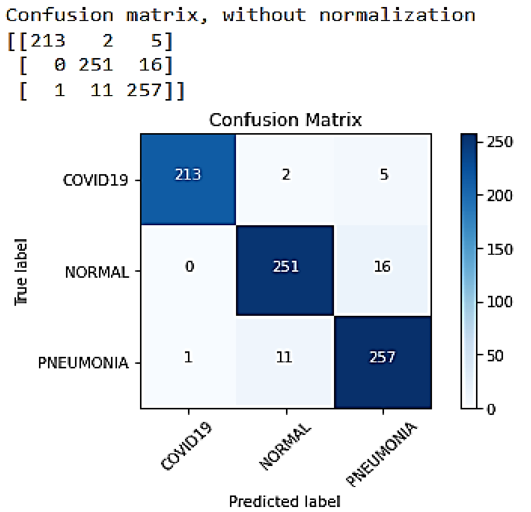

Figure 1: Confusion Matrix.

	precision	recall	f1-score	support
0	1.00	0.97	0.98	220
1	0.95	0.94	0.95	267
2	0.92	0.96	0.94	269
accuracy			0.95	756
macro avg	0.96	0.95	0.96	756
weighted avg	0.95	0.95	0.95	756

Figure 2. Classification Report.

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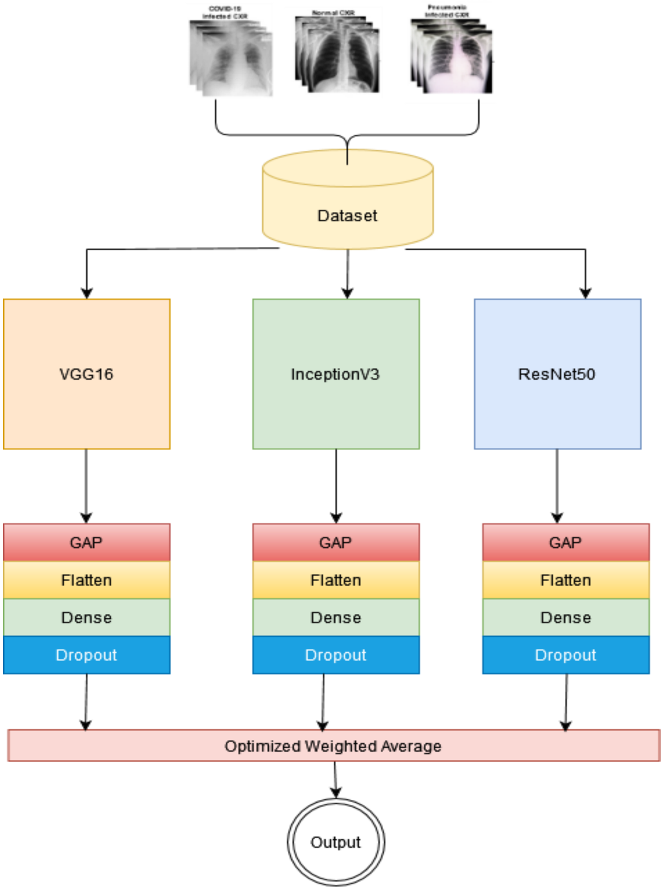

Figure 3: Architecture Diagram of The Proposed Ensemble Model

Algorithm#1: Covid-19 classification using optimized weighted Average Ensemble model.

1. **Input :** X-Ray Images
2. **Output:** Covid-19 Classification
3. **begin**
4 .1 Image ← Read Chest X-Ray Images
5. 2.R - image ← Resize the Image
6.3. Image$_{train}$,image$_{test}$ ← Split R - Image
7.4. Train all three CNN Models Separately
8. CNN – load the model
9. Model ← Train (CNN, Train - image$_{test}$)
10 Confusion Matrix – Prediction (Model, Test – Image$_{Test}$)
11. Print Results, end
12. Load and append all three models (VGG16, InceptionV3, ResNet50) models for average ensemble
13. Model ← Load(Model)
14. Model$_{Append}$ ← Append (Model)
15. Apply Grid Search Algorithm to find optimized weights
16. Select the weights giving highest performance
17. Evaluate the Model $_{Append}$ on Image $_{Test}$
18. Print Results
19. End

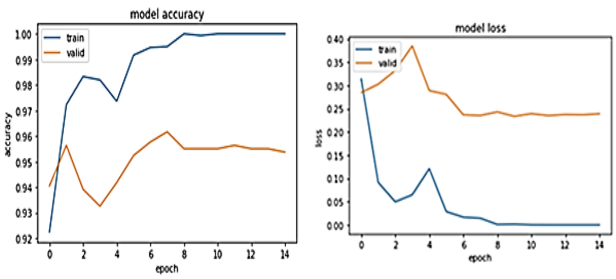

Figure 4: Epoch Vs Accuracy, Epoch Vs Loss Graphs

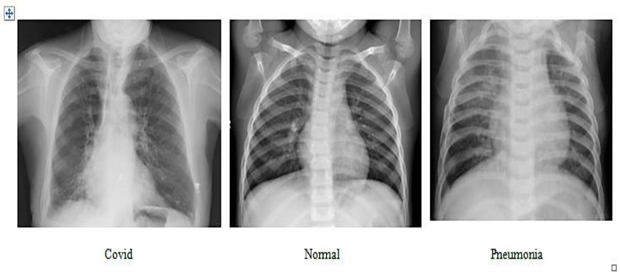

Figure 5: Sample Chest X- Ray Images

4.2 Investigational Setup

The Google Colaboratory is being used which offers 12GB RAM and an NVIDIA Tesla K80 GPU for 8 hours, was cast-off to train and exam the models. Categorical cross-entropy loss functions, "Adam" optimizer with a Learning rate of 0.001 were employed for multi-class classification. Using a batch size of 32, the models were qualified for 25 epochs, and early stopping was used to avoid over fitting. The tolerance for early stopping was set at three iterations, meaning training would end if validation loss did not decrease over those iterations' next three. The performance of multi-class classification is shown in *figures 1* and *2*.

4.3 Results

The study's results are presented in this section. 4 For multi-class classification, three state-of-art models—VGG-16, InceptionV3, and ResNet50—were initially assessed. In order to improve performance, the models were then integrated and adjusted using the weighted average method. For multiclass classification, VGG-16, ResNet50, and InceptionV3 are each evaluated separately and then added to an ensemble model using the aggregate average technique for greater accuracy and prediction. As already noted, the effectiveness of an ensemble model for multi-class organization was evaluated by means of an optimized weighted average grid search was done to find the best weights. *Figure 3* illustrates the ensemble model's architecture.

5. DISCUSSION

In this paper, we have developed an ensemble model with three pre trained models *i.e.*, VGG16, InceptionV3 and ResNet50 We have used this opportunity to tailor this state-of-art models according to our dataset and hyper tuned its parameters with grid search algorithms. We have tried to reduce the layers and computational time. The main agenda of this algorithm to utilize State-of-Art models and customize them to our requirement with best optimized parameters using grid search algorithm.

6. CONCLUSION

In this study, we have developed an ensemble model for Covid19 recognition in Chest X-Ray images. Ensemble models were classified as best models compare to single convolution neural network models. We have received an average rate accuracy of 95.26% for multiclass classification. We have used an optimized weighted average ensemble model along with a grid search algorithm for better hyper parameters.

These types of models help doctors where specialized radiologists are not readily accessible.

Table 2: Comparative study with existing and various techniques

Author	Method	Advantage	Disadvantage
Ismael et al. [22]	*ResNet50 and SVM*	ResNet50 and SVM is good with computational cost	The present technique is not suitable for the large number of datasets.
Jain et al. [23]	Models used are InceptionV3, Xception, and ResNeXt models	Multi-class classification, a variety of models have been developed. Xception model did incredibly well, with a precision of 97.97%.	The best accurateness was got due to over fitting and duplicate imageries used in the dataset,
Saddam Khan et al. [24]	COVIDRENet-1 and COVIDRENet-2 CNN models.	Authors used region edge-based techniques to better extract features from an image.	To calculate the robustness of the suggested method, multi-class organization will also be used. Moreover, the balanced dataset may include duplicate photos.
Bejoy et al [25]	Multi-CNN model	Used various CNN model to receive better accuracy	All possible combinations were not performed
Our Model (Existing)	VGG16+ResNet 50+InceptionV3	Less layers with optimized hyper tuning parameters with grid search with better accuracy with less computational cost	Need to be test on large dataset

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