COV-NET: COVID-19 Detection Using Neural Network

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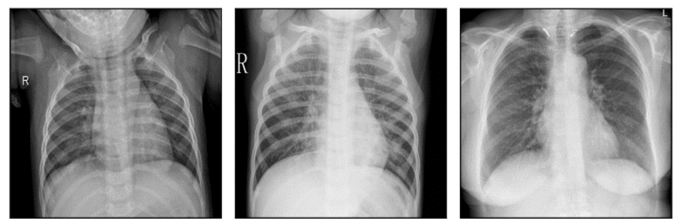
Abstract— In December 2019, the emergence of the novel coronavirus (COVID-19) in Wuhan, China, was traced back to the Phinolophus bat. The virus quickly transmitted to humans and rapidly spread worldwide, ultimately leading to a global pandemic. The impact of the COVID-19 pandemic has been profound, affecting various aspects of our daily lives, including education, the global economy, and transportation. Given the rapid transmission of the disease, early detection of positive cases becomes crucial in preventing further spread and ensuring prompt treatment for affected individuals. However, the availability of accurate automated diagnostic tools remains limited, highlighting the need for auxiliary diagnostic methods. The utilization of artificial intelligence (AI) techniques in conjunction with radiological imaging, such as X-rays and CT scans, holds potential for the accurate detection of COVID-19. In this study, a new dataset for COVID-19 detection was created by merging existing datasets of pneumonia, normal cases, and COVID-19 cases. This dataset addresses the scarcity of COVID-19 data and allows for binary and multi-class classification tasks. Three CNN models, ResNet18, ShuffleNet, and MobileNet, were utilized in the experiments. Ensemble techniques were employed to improve accuracy by combining the predictions of these models. The ensemble of ShuffleNet and MobileNet achieved a remarkable accuracy of 99.8% for COVID-19 and pneumonia detection, while the ensemble of ShuffleNet and ResNet18 achieved 88% accuracy for the multi-class classification of COVID-19, pneumonia, and normal case [1] Code is available at https://github.com/MarihamR/Covid19-Detection.

Keywords—Artificial intelligence, COVID19 (coronavirus), Deep learning, Chest X-ray.

I. INTRODUCTION

The novel coronavirus (COVID-19) pandemic appeared in Wuhan, China in December 2019 and has become a serious public health problem worldwide [1]. At the date of writing of this paper, the COVID-19 virus has spread rapidly in 215 countries causing infected 16,260,482 people, and 649,447 dead cases [2].The virus that caused COVID-19 pandemic disease was called severe acute respiratory syndrome coronavirus 2, also named SARS-CoV-2 [3]. Coronaviruses (CoV) are a large family of viruses that cause diseases resulting from colds such as the Middle East Respiratory Syndrome (MERS-CoV) and Severe Acute Respiratory Syndrome (SARS-CoV). Coronavirus disease (COVID-19) is a new species that was discovered in 2019 and has not been previously identified in humans. Coronaviruses are zoonotic because it is transferred from animals to humans [4]. COVID-19 virus is presumed to be contaminated from bats to humans. Signs of infection include fever, cough, and dyspnea. It also led to complications such as pneumonia, severe acute respiratory syndrome, septic shock, multi-organ failure, and death. Early detection and commencement of treatment in severe cases is key to reducing mortality. So, it is very critical to detect positive cases as early as possible to save infected people's lives. The most common test technique currently used for COVID-19 diagnosis is a real-time reverse transcription-polymerase chain reaction (RT-PCR). Chest radiological imaging such as computed tomography (CT) and X-ray have vital roles in early diagnosis and treatment of this disease [5]. Due to the low RT-PCR sensitivity of 60%–70%, even if negative results are obtained, symptoms can be



(a) Normal *(b) Pneumonia* *(c) Covid*

Figure 1 Chest X-ray Samples from the test datasets

[1] This paper is a result of a course project conducted in June 2020 under the guidance of Dr. Nourelmadany Elmadany for the postgraduate course EC736-Neural Networks Applications.

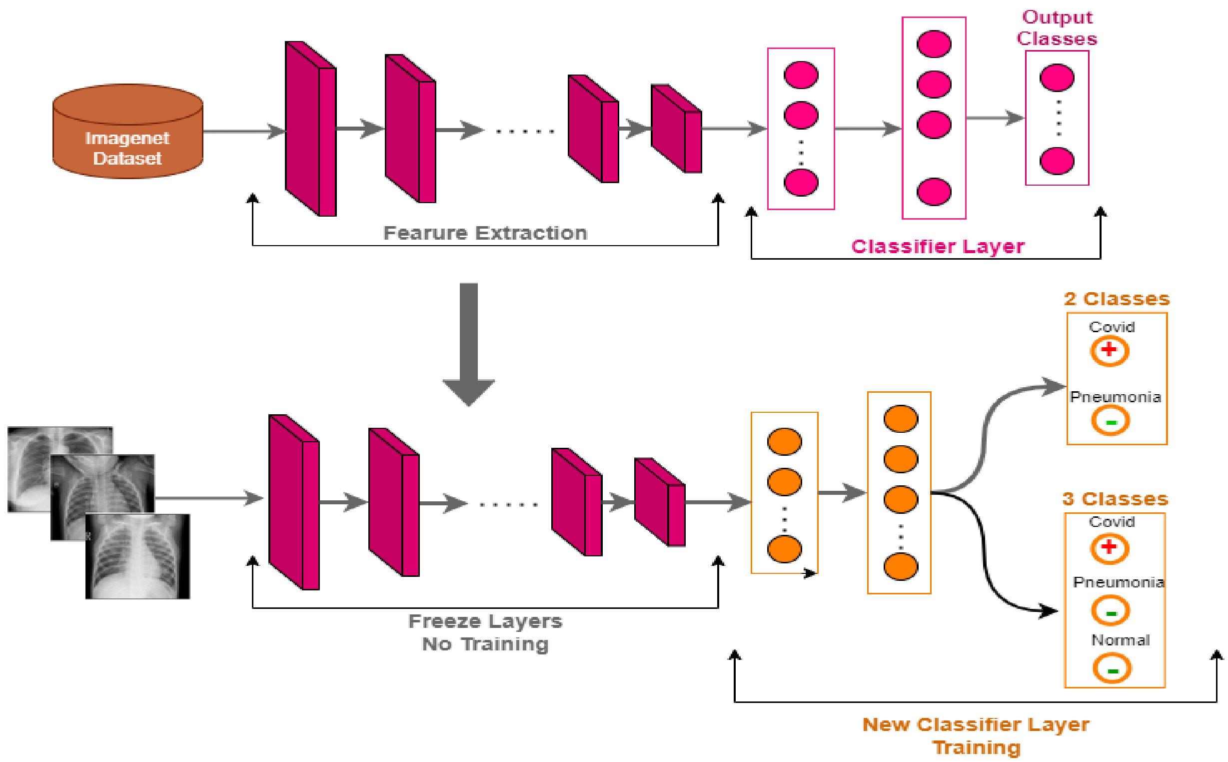


Figure 2: Transfer Learning Model for COVID Detection

detected by examining radiological images of patients [6,7]. It is stated that Chest radiological imaging is a sensitive method to detect COVID-19 pneumonia, and can be considered as a screening tool with RT-PRC [8].

Due to the huge spread of the coronavirus disease and the lack of accurate automated toolkits, the need for auxiliary diagnostic tools is crucial. So, the researchers tried to find other detection methods. One of the most common and effective methods applied by the researchers is the use of CT-Scans and X-rays coupled with the application of advanced artificial intelligence (AI) techniques to provide accurate detection of this disease. It can also be assistive to overcome the problem of a lack of specialized physicians in remote villages.

Recently, many radiology images have been widely used for COVD-19 detection. Hemdan et al. [9] used deep learning models to diagnose COVID-19 in X-ray images and proposed a COVIDX-Net model comprising seven CNN models. Wang and Wong [10] proposed a deep model for COVID19 detection (COVID-Net), which obtained 92.4% accuracy in classifying normal, non-COVID pneumonia, and COVID-19 classes. Ioannis et al. [11] developed the deep learning model using 224 confirmed COVID-19 images. Their model achieved 98.75% and 93.48% success rates for two and three classes, respectively. Narin et al. [12] achieved a 98% COVID-19 detection accuracy using chest X-ray images coupled with the ResNet50 model. Sethy and Behera [13] classified the features obtained from various convolutional neural network (CNN) models with support vector machine (SVM) classifier using X-ray images. Their study states that the ResNet50 model with SVM classifier provided the best performance. Finally, there are also several recent studies on COVID-19 detection that employed various deep learning models with CT images [14].

In this paper, a new chest X-ray dataset for COVID-19 detection was created by combining two existing datasets, aiming to mitigate the issue of limited availability of COVID-19 detection data. One dataset [15] consists of pneumonia and normal cases, while the other dataset [16] exclusively contains COVID-19 cases. The constructed dataset facilitates the evaluation and development of models for two tasks: binary classification (COVID-19 and pneumonia) and multi-class classification, (COVID-19, pneumonia, and normal). In our experiments, we utilized three CNN models: ResNet18, ShuffleNet and MobileNet. Furthermore, ensemble techniques were employed to improve accuracy by aggregating the predictions from multiple models.

The paper is organized as follows: Section II discusses the dataset constructed for the study. Section III explains the proposed approach. Section IV presents details of the experiments conducted, and Section V reports the results obtained. Finally, Section VI concludes the paper, providing a concise summary of the findings and suggesting future research directions.

II. DATASETS

Due to the limited availability of COVID19 detection data, we collected our experimental data from two different datasets. Firstly, we examined a Kaggle dataset [15] that contains 5,863 X-ray images of children. This dataset is divided into two classes: Normal and Pneumonia. The Pneumonia category includes images of both bacterial and viral pneumonia cases. The training set consists of 1,341 Normal images and 3,875 Pneumonia images. The test set contains 234 Normal images and 300 Pneumonia images. Secondly, we examined the COVID-19 dataset sourced from a GitHub repository [16], which encompasses a collection of 708 X-ray images exclusively focused on individuals diagnosed with Covid19.

To construct our dataset [17], we merged the two aforementioned datasets. In the first dataset, we categorized the images into two folders: Normal and Pneumonia. The training set for each category comprised 700 images, while the test set included 230 images. Furthermore, in the second dataset, we assigned 500 images for training and 208 images for testing, specifically in a separate folder labeled Covid19. In fig. 1, we provide a visual representation of sample images from each class in our dataset.

Given that our primary objective revolves around the early detection of Covid and distinguishing between patients with Covid pneumonia and those with ordinary pneumonia, we partitioned our dataset into two subsets. The first dataset focuses solely on binary classes, namely Covid-Pneumonia, enabling the classification between ordinary pneumonia and Covid pneumonia cases. On the other hand, the second dataset encompasses three classes: normal, pneumonia, and Covid, facilitating a more comprehensive classification framework to identify normal cases, pneumonia cases, and Covid cases.

III. PROPOSED APPROACH

Transfer learning is a powerful technique in deep learning that exploits the knowledge acquired by a pre-trained Convolutional Neural Network (CNN) on a source dataset and applies it to a different, but related, target task with new data, often of a smaller size. The process begins by training a CNN on a specific task, such as image classification, using a large-scale benchmark dataset. This initial training phase enables the CNN to learn informative image features effectively. In the subsequent transfer learning phase, the pre-trained CNN is employed to extract features from a new set of images that belong to a different domain or have a distinct nature. By utilizing the learned knowledge and feature extraction capabilities from the initial training, the CNN can effectively extract meaningful features from the new images, improving performance on the target task.

The proposed approach is illustrated in fig. 2. We start by selecting a pre-trained CNN model, which has been trained on a large-scale dataset like ImageNet dataset [18]. In our approach, we freeze the feature extraction layers of the pre-trained model, which means that we keep their pre-trained weights and do not update them during the training process. The only part of the network that is modified and requires training is the classifier layer. This layer is responsible for mapping the extracted features to the desired output classes. In our proposed approach, the number of output classes depends on the specific classification task. For the Covid-Pneumonia detection, we have two output classes: Covid and Pneumonia. For the detection of normal, pneumonia, and Covid cases, we have three output classes: Normal, Pneumonia, and Covid.

The pre-trained CNN models employed for this study are ResNet18 [19], ShuffleNet V2 [20], and MobileNet V2 [21]. These models have been pretrained on the ImageNet dataset[18], which is a large-scale benchmark dataset widely used in the computer vision community. By utilizing these networks, we aimed to take advantage of their established capabilities in accurately categorizing our dataset. Additionally, to further enhance the performance of our classification task, we implemented an ensemble technique. Ensemble learning involves combining the predictions of multiple models to make a final prediction. By combining the outputs of ResNet18, ShuffleNet V2, and MobileNet V2, we aimed to improve the overall classification performance. The ensemble technique enables us to leverage the strengths and diversity of each individual model, potentially leading to better accuracy and robustness in our classification results.

IV. EXPERIMENTS

A. *Experimental settings*

In this research, a machine equipped with an Intel Core i7-9700 CPU with 8 cores and a Nvidia GeForce GTX-1080Ti GPU was utilized to conduct simulations. The primary scientific computing platform employed in this study was Python. Models were implemented using pytorch.
We trained the models using the RMSprop optimization algorithm with a learning rate of 0.003 and a batch size of 64 and 16 for dataset 1and 2, respectively. The learning rate (LR) is a crucial hyperparameter that determines the extent of weight change in a model during training. However, it can be challenging to select an appropriate LR value. To expedite the model's convergence to an optimal solution, a learning rate scheduler can be utilized. This scheduler modifies the learning rate based on a predefined schedule during training. In our case, we implemented a learning rate scheduler that reduces the LR by a factor of 0.1 every 5 epochs. The categorical cross-entropy loss function was utilized to evaluate the discrepancy between predicted and actual labels. We trained the model for 20 epochs, and monitored the training loss to determine when to stop training.

B. *Preformance metrics*

In this research, we utilized the most common performance metrices used in image classification. Table 1 outlines the performance metrics adopted in our experiments, namely Accuracy, Precision, Recall, and F1-score. The performance metrices were computed in terms of FP, TP, TN, and FN, representing the number of False positives, True Positives, True Negatives, and False Negatives, respectively.

Table 1: The Quantitative Performance Measures Adopted in the Study

Metric	Equation
Accuracy	(TP+TN)/(TP+FP+TN+FN)
Precision	TP/(TP+FP)
Recall	TP/(TP+FN)
F1-score	(precision.recall)/(precision+recall)

V. RESULTS AND DISCUSSION

In this section, we assessed the performance of three convolutional neural network (CNN) models, namely ResNet18, ShuffleNet, and MobileNet, in a binary and multi- class classification tasks. We also evaluated the performance of ensemble techniques. The evaluation metrics employed to assess the model’s included accuracy, precision, F1 score, recall, and the confusion matrix.

Table 2 Results of CNN Models Experimented for Binary Classification

Models	Accuray	Precision	Recall	F1-score
ResNet18	0.9764	0.9764	0.9764	0.9764
Mobilenet_v2	0.9843	0.9843	0.9843	0.9842
Shufflenet_v2	0.9902	0.9904	0.9902	0.9902
ResNet18+Mobilenet	0.9921	0.9921	0.9921	0.9921
Resnet18+Shufflenet	0.9941	0.9941	0.9941	0.9941
Shufflenet+Mobilenet	**0.9980**	**0.9980**	**0.9980**	**0.9980**

Table 3 Results of CNN Models Experimented for Multi-Class Classification

Models	Accuray	Precision	Recall	F1-score
ResNet18	0.8571	0.8602	0.8571	0.8565
Mobilenet_v2	0.8288	0.8266	0.8288	0.8240
Shufflenet_v2	0.8504	0.8573	0.8504	0.8440
ResNet18+Mobilenet	0.8625	0.8612	0.8625	0.8609
Resnet18+Shufflenet	**0.8801**	**0.8789**	**0.8801**	**0.8786**
Shufflenet+Mobilenet	0.8477	0.8493	0.8477	0.8414

The performance metrics for the models on the binary and multi-class classification tasks are summarized in Table 2-3. The table provides an overview of the evaluation outcomes for each model, encompassing accuracy, precision, F1 score, recall, and other pertinent metrics.

The ShuffleNet+MobileNet model demonstrated remarkable performance, achieving the highest accuracy among the other models with an impressive accuracy of 99.8% for binary classification task. Additionally, this model exhibited high precision, recall, and F1 score of 0.998. These results highlight the superior capabilities of the ShuffleNet+MobileNet over the other models. For the three classes task, the combined ResNet18+ShuffleNet model achieved the highest accuracy compared to other models with 88.01%. Furthermore, it demonstrated precision (0.8789), recall (0.8801), and F1 score (0.8786). To gain a comprehensive understanding of the performance differences, we generated confusion matrices (Figures 3 and 4) for the classification tasks using the Shufflenet+MobileNet model for binary class and the ResNet18+ShuffleNet model for multi-class. These matrices highlighted the Shufflenet+MobileNet and ResNet18+ShuffleNet model's superior accuracy in classifying binary and multi-class, respectively compared to the other models.

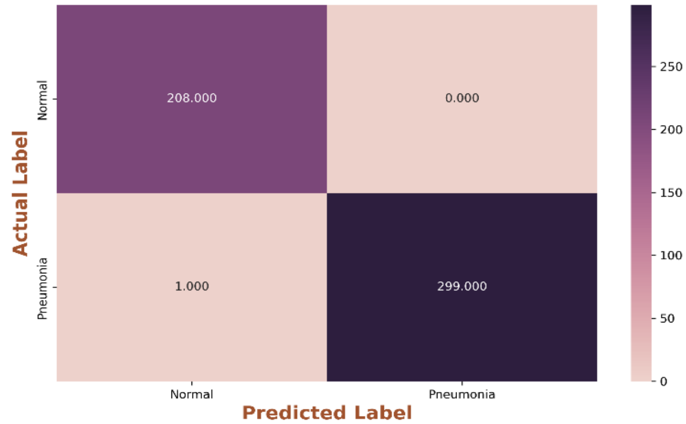


Figure 3: Confusion matrices for binary classification

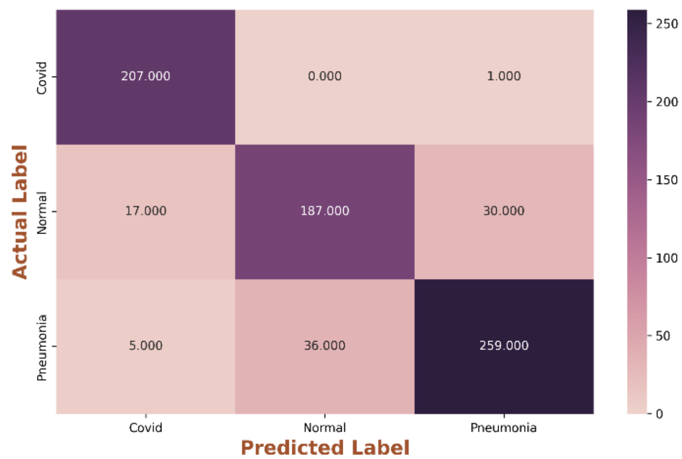


Figure 4: Confusion matrices for multi-class classification

VI. Conclusion

In this study, we proposed a deep learning-based approach for detecting and classifying COVID-19 cases from X-ray images. By utilizing different pre-trained CNN networks as classification models, we achieved high accuracies of 99.8% for the two-class task and 88% for the three-class task. However, a limitation of our study was the limited availability of COVID-19 X-ray images, which is attributed to the novelty of the disease. In future work, we aim to address this limitation by expanding the dataset with a larger number of images. This expansion will particularly benefit the three-class task, allowing for a more comprehensive analysis and improved method performance.

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