Optimising Deep Learning For COVID-19 Detection In Chest X-Rays

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Abstract— ***In order to solve various issues in medical image analysis, deep learning techniques have quickly emerged as a crucial method for medical picture segmentation. This overview discusses some basic concepts and applications and recent advances in deep learning for medical image segmentation. [1] With deep learning, the tasks become easy to handle, including segmentation, registration, recognition of objects, and categorization of images. We emphasize deep learning methods that can be used in segmenting chest X-ray images by providing the domain's basics, applications, and related frameworks. We also present some previous experiences in the sector, using different methodologies that solve problems related to low classification accuracy, low resolution of segmentation, and poor picture enhancement. Medical image analysis is a fast-evolving discipline with a growing need for powerful segmentation algorithms due to the complex nature and inaccuracies associated with medical imaging. Recent developments have shown promise in tackling these issues, especially in deep neural networks. This paper discusses commonly used data and assessment criteria while reviewing the literature on Chest X-ray images using deep custom convolutional neural networks (CNNs), Vgg-19, Mobilenet, and Resnet. This work seeks to direct future research efforts toward improving the effectiveness and reliability of medical picture segmentation algorithms by combining insights from many sources.***

Keywords— *Medical image analysis, deep learning, segmentation, chest X-ray, algorithms, reliability, object recognition, resolution, classification accuracy, neural networks.*

I. Introduction

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, has posed significant challenges to healthcare systems across the world, emphasizing the urgent need for effective disease management strategies. [2] Early and accurate detection is critical for controlling the virus spread and improving patient outcomes. [3] Whereas the standard diagnostic procedure for COVID-19 is by RT-PCR tests, very often these are resource-intensive and time-consuming. Hence, the researchers focused their study on chest X-ray imaging as a fast and inexpensive complementary tool for COVID-19 detection, particularly in regions where RTPCR testing may not be available. By leveraging deep learning—a rapidly advancing field of artificial intelligence—this approach holds the potential to significantly enhance the accuracy and efficiency of COVID-19 diagnosis through chest X-rays. [4] This research aims to provide a faster alternative to traditional testing methods, improve diagnostic accuracy, optimize resource utilization, and support healthcare professionals in delivering better patient care.

This research seeks to develop an optimal deep learning model for the rapid and accurate detection of COVID-19 using chest X-ray images. Our main objectives of the project is to get the highest possible accuracy is identified with the maximization of sensitivity and specificity in the detection of the virus from chest X-rays; the reduction in time taken for diagnosis will be such that decision-making is fast. It should also ensure that resources are utilized in an efficient manner, particularly in low-resource settings. Apart from these, the scalability and ease of access of this model will definitely enable wide deployment in diverse healthcare environments where access to advanced diagnostic technologies is limited.

II. Literature Review

Recent progresses in deep learning strategies have influences on medical imagining, in which the identification of COVID-19 diseases has been noted. Talukder et al. [5] propose a transfer learning model in which ResNet, InceptionResNetV2, Xception, and EfficientNet Excel in COVID-19 classification tasks. Fine-tuning these pre-trained models on COVID-19 datasets resulted in impressive accuracy rates: 99.55% for Xception, 97.32% for InceptionResNetV2, 99.11% for ResNet50, 99.55% for ResNet50V2, 99.11% for EfficientNetB0, and 100% for EfficientNetB4 on a dataset of 2,000 X-ray images. EfficientNetB4 proved to be the most reliable model, and when tested on a larger dataset of 4,350 images, it achieved a precision of 99.13%, recall of 99.16%, and an overall accuracy of 99.17%. These results highlight the model's effectiveness as a diagnostic tool for radiologists dealing with COVID-19 and lung-related diseases.

Karim et al. [6] Deep learning algorithms have been integrated to improve diagnostic capacities in their studies. This work presents a unique deep learning-based computer-aided diagnosis tool for COVID-19 detection from symmetric X-ray data. Convolutional Neural Networks (CNN), the Ant Lion Optimization (ALO) algorithm, and a Multiclass Naïve Bayes (NB) classifier are combined in the suggested method. Also, several classifiers, in addition to CNNs, were evaluated, such as Softmax, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees (DT). In conjunction with ALO and CNN, the NB classifier produced remarkable outcomes, decreasing execution time and claiming 98.31% accuracy, 100% precision, and 98.25% F1 score.

Kaya et al. [7] explored methods such as computed tomography (CT) and chest X-ray imaging, in conjunction with deep learning models, as more accurate detection methods to address the limitations of RT-PCR tests for COVID-19 diagnosis. Recognizing that errors in radiology often arise from uncertainty and time constraints, they emphasized the need for automated and reliable diagnostic tools. Their research proposed a novel computer-aided diagnosis system that integrates the Multiclass Naïve Bayes (NB) classifier and the Ant Lion Optimization Algorithm (ALO) with Convolutional Neural Networks (CNN). Several other classifiers were evaluated for comparison, including Softmax, Support Vector Machine (SVM), K-Nearest

Neighbors (KNN), and Decision Tree. The CNN-NB combined with ALO demonstrated superior performance for rapid and accurate COVID-19 detection, achieving remarkable results: 98.31% accuracy, 100% precision, and an F1-score of 98.25%, all while maintaining the shortest execution time.

Haghanifar et al.[8] conducted a study to evaluate a model known as COVID-CXNet, which is based on CheXNet and aims to identify COVID-19 using chest X-rays. They enhanced the model by applying methods like CLAHE and BEASF to boost the contrast of images. This approach helped the model reach an impressive accuracy rate of 96.10% when tested, showing it can be pretty effective in diagnosing COVID-19-related pneumonia. The team also used visual tools like Grad-CAM and LIME to ensure that the model focused on the correct areas of the X-rays when making decisions. Despite challenges like a limited number of available images, COVID-CXNet performed well compared to other models. This suggests that advanced models like this could be very beneficial in detecting COVID-19 in areas with limited medical resources.

III. PROPOSED SYSTEM

Our COVID-19 detection system utilizes a comprehensive approach that leverages chest X-ray images and deep learning techniques. First, the system processes these images using a deep learning model designed to identify and classify signs of COVID-19 infection. Relevant features are extracted from the images, and all pertinent data is temporarily stored for further evaluation. To improve accuracy, we fine-tune various pre-trained models, such as Xception, ResNet, and EfficientNet, specifically on COVID-19 datasets. The system also incorporates performance metrics like precision, recall, and F1-score to assess its effectiveness. The outcomes of the detection process include confirmed COVID-19 cases and classifications of other lung-related diseases. Figure 1 provides an overview of our proposed detection system.

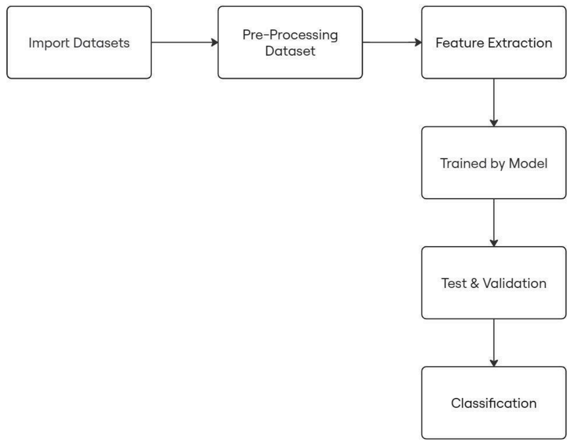

Fig. 1. Overview of the system.

A. Dataset

COVID-19 has evolved as an emergency, demanding a rapid diagnostic system that can be quickly deployed worldwide. Given the development of an artificial intelligence-based diagnosis system, we have compiled this diverse set of CXR images from multiple sources, including research articles and publicly available datasets. The research was done to compile a dataset that the research fraternity would use to train CNN models in automated diagnosis. This dataset has been utilized in the COVID-19 Lite paper with promising results by proposing a novel CNN-based solution for improving diagnostic accuracy.

Chest X-ray images are in the PA view, with classes defined for Normal, Virus, and patients affected by COVID-19. The CXR images are 7,565. Further, 465 other COVID-positive patient images were collected from nearby hospitals to make the class-wise representation adequate. This dataset is curated to provide suitable training and testing of machine learning models. This dataset will help in quicker and more valid diagnosis of COVID-19 and other respiratory diseases.

Table I. DATASET

Class Name	Number of Images
Virus	1964
Normal	2009
Covid	4057
Total	8030

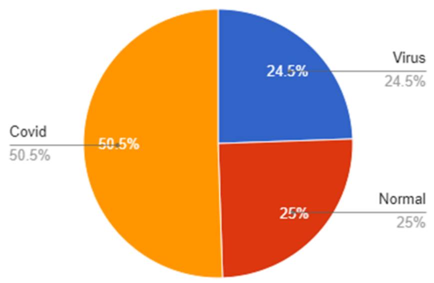

Fig 2: Dataset Class Distribution balance pie chart

B. Data pre-processing

In order to prepare raw data for model training, it must be cleaned, arranged, and transformed. This work improves dataset diversity through data augmentation (rotation, flipping, and zooming), and it also resizes CXR images for uniformity. Identifying COVID-19 from CXR pictures, which facilitates early diagnosis and therapy, depends heavily on image classification. Three deep learning models are employed: an ensemble model to increase detection accuracy and distinguish between COVID-19, pneumonia, and negative cases; convolutional neural networks for feature extraction; and ResNet for recognizing complicated characteristics.

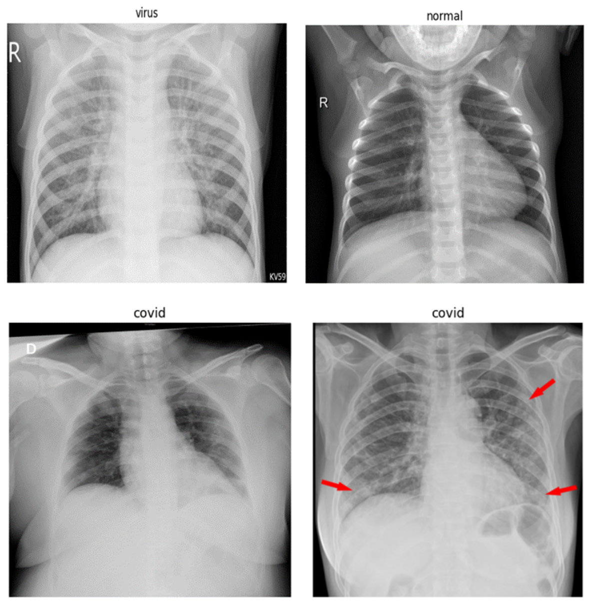

Fig 3: CXR Images after pre-processing

C.Machine Learning Models

Custom CNN

A custom CNN was designed for image classification in this project. Input images were resized to 224x224 pixels, followed by Conv2D layers with 32 filters and activation functions to introduce non-linearity. The network included multiple convolutional, activation, and max pooling layers for feature extraction, and dense layers for learning complex patterns. The output layer, with three units, classifies images into three categories. The dataset was shuffled for each epoch, and early stopping with a patience of 10 was applied. The model trained with a batch size of 32 and 50 epochs, stopping when the validation error plateaued.

Mobile Net V2

MobileNetV2, designed for mobile and embedded devices, is a lightweight model that uses depthwise separable convolutions to reduce complexity and speed up processing. Our project adapted a pre-trained MobileNetV2 model from ImageNet by removing the top layers and resizing input images to 224x224x3. The model's output was flattened and passed through fully connected layers with 1024, 512, and 256 units, each using ReLU activation. A final softmax layer classified the images into three categories, offering an efficient solution for real-time image classification tasks.

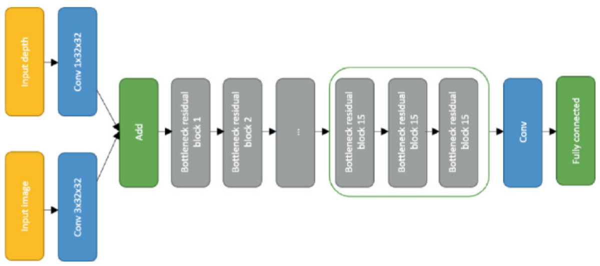

Fig 4: Architecture of MobileNet V2

EfficientNet

EfficientNetB0 is a lightweight deep learning model committed to scaled-up depth, width, and resolution to achieve much better performance with fewer parameters. Given its efficacious scaling of depth, width, and resolution, the work applied EfficientNetB0 as the base model for image classification. EfficiencyNet B0 was pre-trained on ImageNet, adapted by removing the top layers and setting the input images at 224x224x3 dimensions. The output from the base model was flattened and then passed through a set of fully connected layers with units of size 1024, then 512, then 256, using all ReLU activation functions. A softmax layer with three classes predicted the final output.

VGG-19

VGG-19 is a convolutional neural network consisting of 16 convolutional layers with 5 pooling layers and 3 fully-connected layers. It is famous for its simplicity and effectiveness in solving image classification problems. Considering the detection of COVID-19, the VGG-19 model was fine-tuned in assessing CXR images.

The model processes the input images via multiple convolutional and pooling layers to extract relevant features and finally classifies the photos such as COVID-19, pneumonia, or normal using fully connected layers. Its depth and architecture also make it quite suitable for finding very subtle patterns in medical imaging, thus helping to identify COVID-19 correctly.

Fig 5: Architecture of VGG-19

We used the following Hyperparameters for the VGG-19 Model to ensure optimal performance in detecting COVID-19.

ResNet50

ResNet-50 is a deep convolutional neural network elaborated with residual connections, helping to overcome the vanishing gradient problem that always pops up when dealing with intense networks. It is made up of 50 layers.

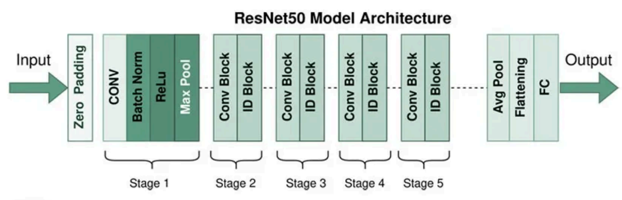

Fig 6: Architecture of RESNET-50

The architecture balances depth and complexity perfectly, resulting in outstanding performance while classifying images. In this respect, ResNet-50 has been used for COVID-19 detection, analyzing chest X-ray images with its robust feature extraction capabilities to classify image data effectively.

Table II. HYPERPARAMETER VALUES OF ALL MODELS

Hyperparameter	Value
Input Shape	Custom (224x224x3)
Batch Size	32
Number of Epochs	50
Dense Layers	1024, 512, 256 units
Loss Function	Categorical Crossentropy
Learning Rate	Default (adaptive)

III. Result and Discussion

We have obtained the performance metrics for classification, including accuracy, recall, Precision, and F1 score individually for EfficientNetV2, InceptionResNetV2, and NasNetLarge. All of these metrics can be calculated using the following equation:

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

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

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

$$\text{F1 Score} = \frac{2 * Precision * Recall}{Precision\ + Recall}$$

Here, TP=True Positive, TN=True Negative, FP=False Positive, FN=False Negative.

Precision is more likely to correctly identify positive instances and recall capture all positive instances. Accuracy is the ratio of correct predictions to the total number of instances. An F1 score is the balance between precision and recall.

We visualized data to better understand the performance of the classification models and uncover trends in chest X-ray images. This approach makes it easier to spot patterns, like the differences between positive and negative cases, and to see where our models are doing well or facing challenges. These visual insights improve our analysis and help us share our findings more effectively with others in the research community.

The confusion matrices matrix outlines how well the models classified instances into three categories, highlighting both correct predictions and misclassifications. Notably, ResNet50 and EfficientNet-B0 demonstrate strong performance with fewer misclassifications, suggesting they better understand distinguishing between the classes. In contrast, the Custom CNN and MobileNetV2 matrices reveal some confusion, particularly in specific classes, indicating areas where these models might need further refinement.

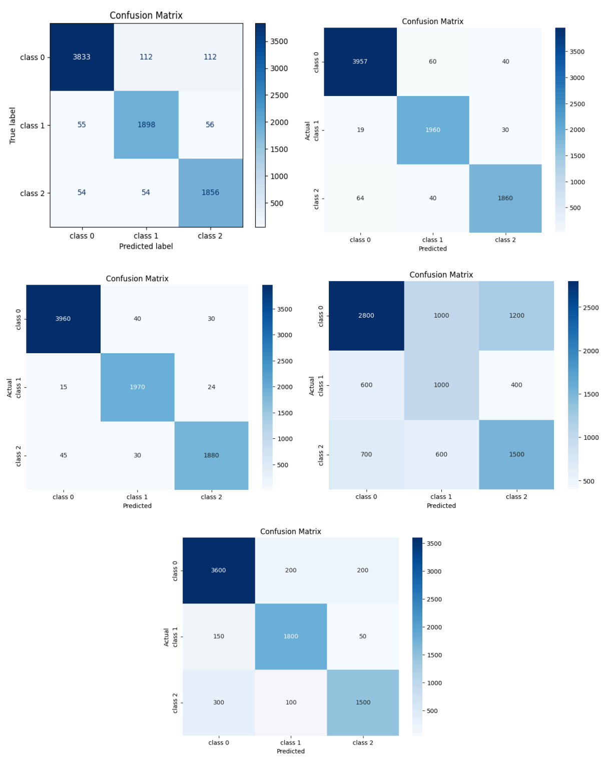

Fig 7: Confusion Matrix of Custom CNN, Mobile NET V2, VGG-19, EfficientNet-B0, ResNet50

It's clear that while VGG-19 performs decently, it still has some moderate misclassifications. This analysis underscores each model's varying strengths and weaknesses in the context of COVID-19 detection. The findings suggest that ResNet50 and EfficientNet-B0 could be more reliable for this task, as they consistently yield more accurate predictions. Meanwhile, Custom CNN and MobileNetV2 may benefit from additional training or adjustments to enhance their performance in accurately identifying cases. Overall, these insights are crucial for guiding future model selections and improvements in this area of research.

The ROC curve (Receiver Operating Characteristic curve) is an essential tool for assessing the performance of binary classification models. It illustrates the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) across different thresholds. The closer a model's ROC curve is to the upper-left corner, the better its performance. In comparing five models—Custom CNN, MobileNet V2, VGG-19, EfficientNet-B0, and ResNet50—it becomes apparent that EfficientNet-B0 and ResNet50 exhibit the strongest performance, with their curves positioned above the others.

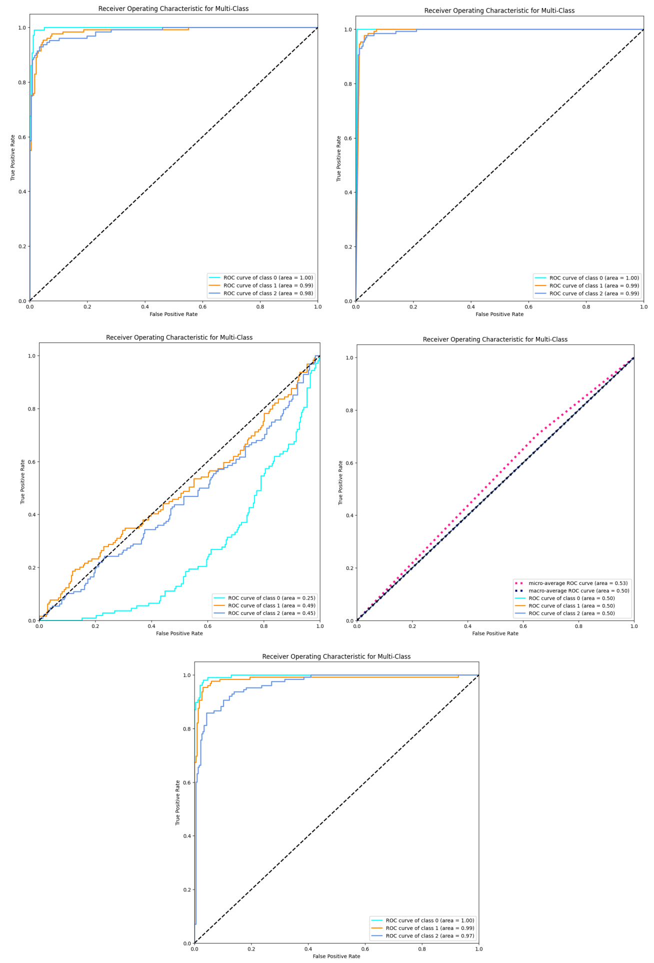

Fig 8: ROC curve of Custom CNN, Mobile NET V2, VGG-19, EfficientNet-B0, ResNet50

Custom CNN and MobileNet V2 lag, indicating less effectiveness in accurately classifying positive instances while minimizing false positives. VGG-19 demonstrates competitive capabilities but doesn't quite match the efficiency of ExcellentNet-B0 and ResNet50. This comparison emphasizes the advantages of leveraging modern model architectures that optimize depth and efficiency, improving accuracy in real-world applications.

Given the computational demands of deep learning models, maintaining a balance between accuracy and speed was essential in implementing our COVID-19 detection system. Our system can run on both CPU and GPU, though using a GPU is necessary to achieve the speed required for real-time analysis. We implemented and tested the system using OpenCV's DNN (Deep Neural Network) module on an Nvidia 1050Ti 4GB GPU. Since the OpenCV library doesn't support GPU by default, we compiled it from the source code to enable GPU support, ensuring faster and more efficient processing of medical images.

TABLE III. PERFORMANCE METRICS OF ALL MODELS

ML model	Accuracy	Precision	Recall	F1 Score
Custom CNN	94.48%	0.95	0.94	0.95
MobileNet	95.41%	0.96	0.95	0.95

VGG-19	97.49%	0.98	0.97	0.97
EfficientNetB0	54.08%	0.57	0.54	0.55
Resnet50	87.34%	0.91	0/88	0.88

The table summarizes a model's classification results, outlining true positives, false positives, and false negatives across three classes. Each cell reflects the counts of predictions, with diagonal values indicating correct predictions, while off-diagonal values represent misclassifications. For instance, class 0 shows many true positives and significant misclassifications with classes 1 and 2. Similarly, classes 1 and 2 detail their respective correct and incorrect predictions, illuminating the model's strengths and areas needing improvement in accurately recognizing each class. Overall, the table visualizes the model's performance in distinguishing between these categories.

TABLE IV. HYPERPARAMETER VALUES' RANGES FOR VGG-19,

Hyperparameter	**Value Range**	**Optimized Value**
Batch Size	16 - 128	32
Weight Decay	1e-6 - 1e-2	1e-4
Learning Rate	0.001 - 0.1	0.001
Dropout Rate	0.2 - 0.5	0.4
Momentum	0.8 - 0.99	0.9
Optimizer	SGD, Adam	SGD
Learning Rate Scheduler	Step, Cosine, ReduceLROnPlateau	ReduceLROnPlateau

IV. CONCLUSION

This project highlights the potential of machine learning in improving COVID-19 detection through chest X-ray analysis. We achieved notable accuracy by employing various models like Custom CNN, MobileNet, VGG19, EfficientNet, and ResNet50, particularly with VGG19 and MobileNet. However, challenges such as data authenticity and model biases were encountered, emphasizing the importance of high-quality data and rigorous validation. The insights gained here can guide future advancements in medical AI, aiming for reliable diagnostic tools while addressing ethical concerns. Ultimately, this work demonstrates the transformative role of AI in healthcare diagnostics, paving the way for innovations that enhance patient care and public health efforts.

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