Multi-Classification Convolution Neural Network Models for Chest Disease Classification

Noha Ayman[1], Mahmoud E. A. Gadallah[2], Mary Monir Saeid[3]
Department of Computer Science-Faculty of Computers and Artificial Intelligence, Fayoum University, Egypt[1]
Egypt Department of Computer Science, Modern Academy for Computer Science and Management Technology, Cairo, Egypt[2]
Department of Information System-Faculty of Computers and Artificial Intelligence, Fayoum University, Egypt[3]

***Abstract*—Chest diseases significantly affect public health, causing more than one million hospital admissions and approximately 50,000 deaths annually in the United States. Chest X-ray imaging technology, which is a critically important imaging technique, helps in examining, diagnosing, and managing chest conditions by providing essential insights about the presence and severity of disease. This study introduces a novel chest X-ray classification framework leveraging a fine-tuned VGG19 model (16 layers) enhanced with CLAHE for improved contrast, binary mask attention to highlight abnormalities and advanced data augmentation for better generalization. Key innovations include the use of a Probabilistic U-Net for lung segmentation to isolate critical features and weighted masks to focus on pathological regions, addressing class imbalance with computed class weights for fair learning. By achieving 95% accuracy and superior class-specific metrics, the proposed method outperforms existing deep learning approaches, providing a robust and interpretable solution for real-world healthcare applications, where a test accuracy of 94.8% is achieved using different customized models based on VGG19 without using a mask. The experimental results indicate that our proposed method surpasses current deep learning techniques in terms of overall classification accuracy for chest disease detection.**

Keywords*—Convolution neural network; classification; chest X-ray; image preprocessing; U-Net; deep learning

I. Introduction

Chest pain is the most common reason for consultations and emergency room visits. Globally, chest radiography is the most frequently used imaging examination, essential for the screening, diagnosis, and management of numerous life-threatening thoracic conditions. The expertise and observational skills of radiologists are crucial for interpreting chest X-rays (CXRs). However, the complexity of the pathologies and the subtle differences in lung lesions mean that even experts can sometimes miss minute details. Additionally, there is a shortage of trained and experienced radiologists. Consequently, recent research has focused on developing systems to detect thoracic diseases and generate reports. These studies predominantly employ deep learning and neural network models. This paper aims to explore these diseases accurately.

The chest is the upper part of the trunk. It gets support from the rib cage, the girdle of the shoulder, and the spine that also protects it. It is the region of the body formed by the sternum, the thoracic vertebrae, and the ribs [1]. It resides between the neck and diaphragm excluding the upper limb. The heart and lungs reside in the thoracic cavity, as well as many blood vessels that play a vital role in feeding (esophagus), breathing, and pumping blood to all parts of the body [2].

Deep learning techniques that implement deep neural networks became popular due to the increase in high-performance computing facilities. Deep learning achieves higher power and flexibility due to its ability to process a large number of features when it deals with unstructured data [3].

Deep learning models have been used successfully in many areas such as classification, segmentation, and lesion detection of medical data. Analysis of image and signal data obtained with medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and X-ray with the help of deep learning models [4]. As a result of these analyses, detection and diagnosis of diseases such as diabetes mellitus, brain tumor, skin cancer, and breast cancer are provided convenience [5].

The contributions of this research can be summarized as follows:

- A method has been devised based on the VGG19 model for the classification of chest X-ray images as COVID, Lung Opacity, Normal, and Viral Pneumonia.
- Preprocessing of images using CLAHE, Data Augmentation, etc., has been considered for improving X-ray image quality to enhance the model performance.
- Attention mechanism is employed here by first generating binary masks that tune the model to learn regions of interest for better detection of pathological features.
- Class weighting while training was done to handle class imbalance, hence the model performed well on all categories.
- VGG19 was pre-trained on ImageNet and fine-tuned on chest X-ray images with very good generalization and a validation accuracy of 95%.

This paper is organized as follows. The Literature survey is given in Section II. Section III describes the Methodology that is used. The result is presented in Section IV. Conclusions and future work are provided in Section V.

II. Literature Survey

Many papers proposed chest disease detection and classification using deep learning techniques. For instance, Wang et al. [6] proposes COVID-Net, a deep convolutional neural network to enable the detection of COVID-19 cases from CXR images. COVID-Net leverages an open human-machine collaborative design strategy, marrying both principled network prototyping with machine-driven exploration utilizing a novel lightweight architecture enhanced in representational capacity and computational efficiency. It was then trained on COVIDx, the benchmark dataset of 13,975 CXR images, incorporating data from five public repositories. Quantitatively, COVID-Net achieved 93.3% accuracy, 91% sensitivity, and 98.9% positive predictive value for COVID-19 detection, outperforming traditional models such as VGG-19 and ResNet-50 in terms of computational efficiency and sensitivity. A qualitative audit using the GSInquire explainability method confirmed that its decision-making relied on clinically relevant lung regions, thus providing transparency and reliability. Though limited by available data, and non-production ready, the core ideas presented in COVID-Net present a very nice starting point to advance further the use of AI approaches for COVID-19 screening, and triaging with possible extension to risk stratification.

In research [7], the author introduce CoroNet, a deep convolutional neural network (CNN) model, was introduced for detecting COVID-19 infection using chest X-ray images. Using the Xception architecture pre-trained on ImageNet dataset, the study trained CoroNet on a curated dataset of COVID-19, bacterial pneumonia, viral pneumonia, and normal chest X-rays. The model achieved an accuracy of 89.6% for four-class classification (COVID-19, bacterial pneumonia, viral pneumonia, and normal); 95% for three-class classification; and 99% for binary classification (COVID-19 vs. others). CoroNet performed better than previous studies, particularly in detecting COVID-19 patients. However, the study acknowledges its limitations, including reliance on a small dataset, and indicates the need for access to larger datasets.

In study [8], the author brings to light the importance of preprocessing the chest X-ray images for better classification of diseases. Using the ChestX-ray8 dataset, this research identifies some quality issues in images that affect classification performance. Prior methods used CNNs with preprocessing techniques such as contrast enhancement and feature extraction, often relying on metadata or manual preparation. In this paper, an automated preprocessing method is proposed that combines Sobel and Scharr edge detection with a shallow CNN to classify images into clear and low-quality images. It achieved 95% accuracy and provided a scalable solution for dataset cleaning and reduced dependence on metadata, although it had problems with extreme image defects.

In study [9], the use of transfer learning for pneumonia classification from chest X-ray pictures is examined, with a focus on differentiating between SARS-CoV-2, generic viral, and bacterial infections as the origins of pneumonia. This study assesses 12 well-known ImageNet pre-trained neural network models, building on earlier studies that frequently concentrated on binary categorization (COVID-19 versus healthy) or required particular data preprocessing. Using a dataset of 6,330 publicly sourced images, cropped to uniform dimensions, and separated into four classes—healthy pneumonia, bacterial pneumonia, viral pneumonia, and COVID-19—these models were optimized. MobileNet v3 demonstrated good classification performance and computational efficiency, with the best F1 score of 84.46%. Additionally, resilience tests were performed by reducing the amount of available training data to 50%, 20%, and 10%, showing varying levels of performance loss. The paper highlights the effectiveness of transfer learning in medical diagnosis while highlighting a number of challenges, such as model convergence issues and data scarcity. Expanding the datasets to different types of lung disorders and establishing preprocessing methods to reduce classification errors are future priorities.

In study [10], this work fills important gaps in previous work on deep learning-based COVID-19 identification, including restricted attention to binary or three-class classification problems, imbalanced datasets, and limited metric reporting. With confidence fusion, it suggests COVDC-Net, a hybrid deep learning model that combines MobileNetV2 and VGG16. On balanced datasets, it performs better, with 96.48% accuracy for three classes and 90.22% accuracy for four classes. The work overcomes the drawbacks of single architectural techniques and ensures scalability for practical clinical applications by providing comprehensive metrics for each class and enhancing model robustness through fusion.

In study [11], Sahin et al, a novel CNN model for COVID-19 detection utilizing chest X-ray pictures is proposed and tested on a dataset of 13,824 images alongside MobileNetV2 and ResNet50. After standardizing the images to 224 x 224 pixels through preprocessing, the models were trained with the Adam optimizer using the same training/testing splits (80%/20%). The proposed CNN outperformed MobileNetV2 (95.73%) and ResNet50 (91.54%) with an F1 score of 97% and test accuracy of 96.71%. It was also computationally economical, using fewer convolutional layers and parameters. The model was limited to single image slices and lacked severity classification capability, which hindered its ability to differentiate between COVID-19 and other viral pneumonia despite its high accuracy. This study highlights the potential of deep learning for COVID-19 diagnosis while addressing gaps like dataset limitations and computational efficiency.

In study [12], it presents a framework for detecting COVID-19 from chest X-ray images using transfer learning, addressing key limitations of prior studies. What was done: The authors used pre-trained VGG19 and EfficientNetB0 models to classify chest X-ray images as COVID-19 or normal in binary classification and extended it to a 4-class task (COVID-19, normal, viral pneumonia, and lung opacity). How it was done: Preprocessing included histogram equalization, CLAHE, and complement techniques to enhance image quality, while segmentation utilized lung masks for region-specific analysis. Training was performed with fine-tuned CNN models using benchmark datasets (e.g., COVID-19 Radiography Database) divided into training, validation, and testing sets. Results achieved: The VGG19 model achieved the best binary classification accuracy of 95% with CLAHE-enhanced images and 93.5% for 4-class classification using EfficientNetB0. Sensitivity, specificity, and F1 scores were also high, demonstrating reliable performance. Limitations or gaps: The study highlights that classification accuracy on segmented images was lower than on full images, suggesting the need for further optimization. Additionally, dataset diversity and scalability remain areas for future research.

III. Methodology

Apply deep learning models to train data and achieve a high accuracy, through datacollecting and make preprocessing on it, then train data. In this section, the proposed method for chest disease classification using chest X-ray images is presented shown in Fig. 7. The data is split to 70 train, 15 validation and 15 test.

A. *Dataset*

As emphasized in the companion paper [11], it is our aim to optimize the performances of the models proposed there. The dataset for this study was the COVID-19 Radiography Database, a large repository of thousands of publicly available benchmark X-ray images of both lungs along with ground-truth masks. In order to make the set of images uniform for efficient processing/analysis, images are available in PNG format with 299 × 299 pixel resolution.

The database consists of 6012 lung opacity images, 10,192 normal cases, 3616 positive COVID-19 cases, and 1345 viral pneumonia cases as depicted. The database was developed by a team from Qatar University and Dhaka University in Bangladesh with collaborators from Malaysia and Pakistan of medical experts. The many classifications of the COVID-19 Radiography [13] Database are represented through samples in Fig. 1.

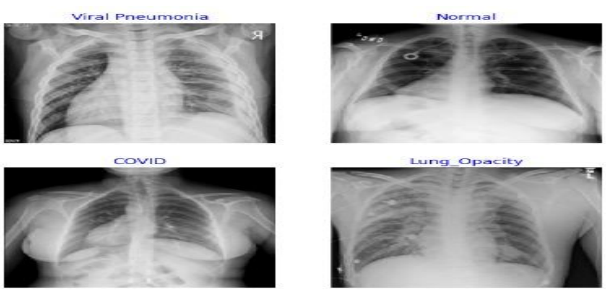

Fig. 1. Sample of the X-ray images used in dataset.

B. *Data Preprocessing*

Preprocessing is kind of important to increase the quality of an image and hence boost the performance of the model. The following steps are performed on the dataset:

- Apply CLAHE (Contrast Limited Adaptive Histogram Equalization)
- CLAHE improves the overall contrast of the chest X-ray images but at the same time, it enhances darker areas particularly. It enhances the contrast of the weak patterns like lesions and opacities and makes the abnormalities conspicuous as shown in Fig. 2.

Image Transformations (Data Augmentation):

Also, in order to increase the variance of the dataset and prevent overfitting, the following operations are performed: rotation, flipping, zooming, and changes in brightness. These changes allowed the model to generalize better over unseen data.

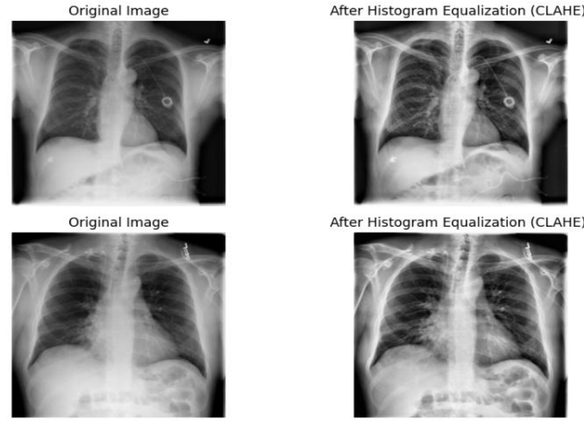

Fig. 2. Image after and before Histogram Equalization.

C. *Attention Mechanism*

In order to draw the model's attention to critical regions in X-ray images during learning, a binary mask-based attention mechanism was implemented as follows:

Mask attention steps:

1) Creating a binary mask: The masks were then converted to binary 0 or 1 based on a threshold value. Regions containing abnormalities were labeled as class 1, while regions containing no abnormalities were labeled as 0.

2) Weighted mask application: The binary mask was then adjusted using the following formula: This calculation is represented by Eq. (1).

$$\text{Weighted mask} = \text{mask} + 0.4 * (1-\text{mask}) \tag{1}$$

- The alpha parameter (0.4) was applied to weight the non-masked (background) regions; thus, the model gives greater importance to abnormal regions but doesn't completely ignore the rest.
- Masked image: The weighted mask was applied to the input image to emphasize pathological regions. This calculation is represented by Eq. (2)

$$\text{Masked image} = \text{image} * \text{weighted mask} \tag{2}$$

- This approach made the model focus on relevant clinical features, resulting in better performance. As shown in Fig. 3.

D. *Weights for Classes in Unbalanced Data*

Fig. 4 shows how the dataset was imbalanced, with the number of images associated with COVID-19 being less than those associated with normal or lung opacity classes. To overcome this, class weights were calculated and passed during model fitting: This calculation is represented by Eq. (3)

$$\text{class\_weights} = \{\text{class\_id}: \text{total\_samples} / (\text{num\_classes} * \text{samples\_in\_class})\} \tag{3}$$

By penalizing misclassifications of underrepresented classes, these class weights ensured that the model learned as equally as possible for each class.

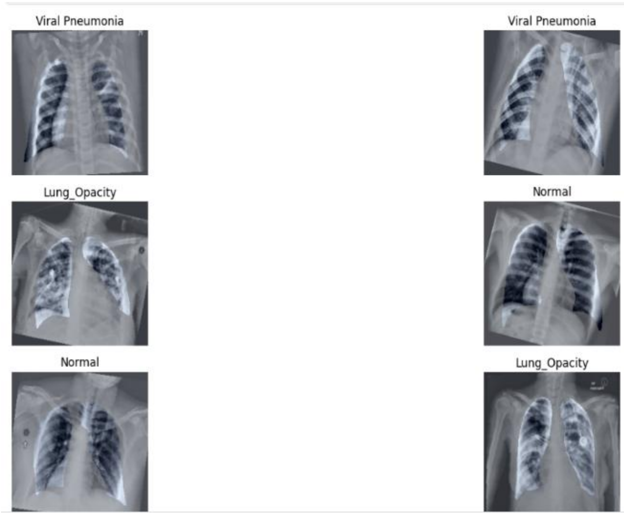

Fig. 3. Image after multiplication the mask.

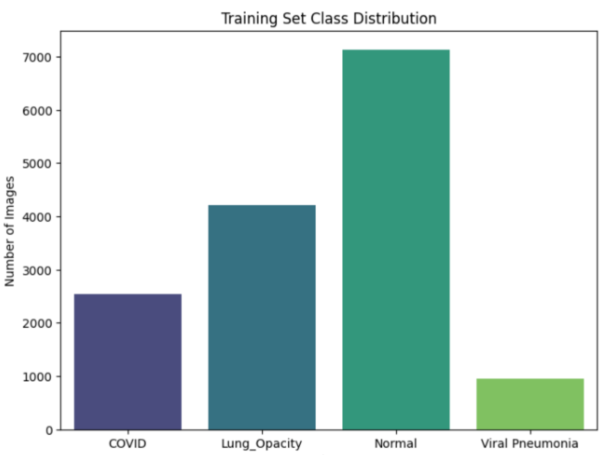

Fig. 4. Different classes in the training dataset.

In this study, CNN models were trained using several versions of segmented and original chest X-ray images as inputs. Both the raw and segmented lung X-ray pictures, as well as improved versions of these datasets, were used in the experiments. CNN models that had already been trained, especially VGG19, were used in the classification procedure. The most successful model was chosen as the final framework after the models were assessed using a variety of performance indicators. The pre-trained models used are briefly described in the sections that follow.

1) VGG19 Model: The VGGNet (Visual Geometry Group Network) is a deep neural architecture characterized by multiple processing layers. What makes VGG-19 particularly effective is its straightforward design, which incorporates stacked 3 × 3 convolutional layers that increase in depth. The network manages dimensional reduction through strategically placed max pooling layers [14]. The architecture includes two fully connected (FC) layers, each containing 4096 neurons. During training, the network extracts features using convolutional layers, while accompanying max pooling layers help reduce the dimensionality of these features. The initial convolutional layer processes input images using 64 kernels, each with a 3 × 3 filter size, to extract features. The network then utilizes fully connected layers to organize these features into a vector format.

Fig. 5 shows the architecture of VGG19. The diagram consists of a series of vertical bars representing different layers in the network: peach-colored bars indicate 3×3 convolutional layers, light blue bars represent max pooling layers, green bars show fully connected layers, and a final red bar represents the SoftMax output layer [15].

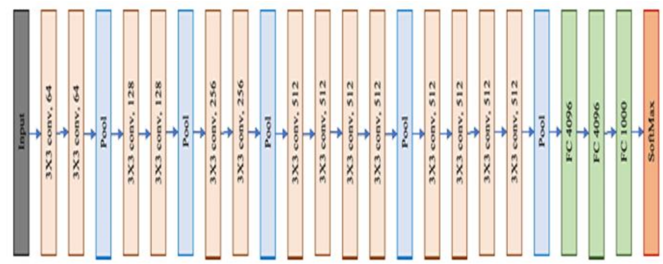

Fig. 5. Architecture of VGG19 [16].

E. Fine-Tuning VGG19 (16 Layers)

- The pre-trained VGG19 model was used (from ImageNet) with fine-tuning on top 16 layers
- The previous layers were frozen to retain general image feature extraction capabilities as shown in Fig. 6.

The last layers were thawed and fine-tuned on the chest X-ray dataset to specialize in features radiography.

Fine-tuning allowed the model to take advantage of the pre-learned weights in adaptation to domain-specific patterns like lung lesions or opacities.

2) Result of fine-tuning: Fine-tuning greatly improved the model performance, resulting in better accuracy and F1 score for all classes. Validation accuracy leveled off at 95%, indicating great generalization.

F. Image Segmentation Using Probabilistic U-Net

Goal: To segment the lung regions and then feed them into the classification model for better feature extraction.

Procedures Adopted:

1) Segmentation model: A Probabilistic U-Net was used to generate masks of the lung region from chest X-rays as shown in Fig. *7*.

2) Mask overlay: The generated segmentation masks were applied to pre-process images by isolating lung regions.

3) VGG19 integration: The segmented images were then passed through the classification pipeline, reducing the impact of irrelevant regions and generally improving accuracy.

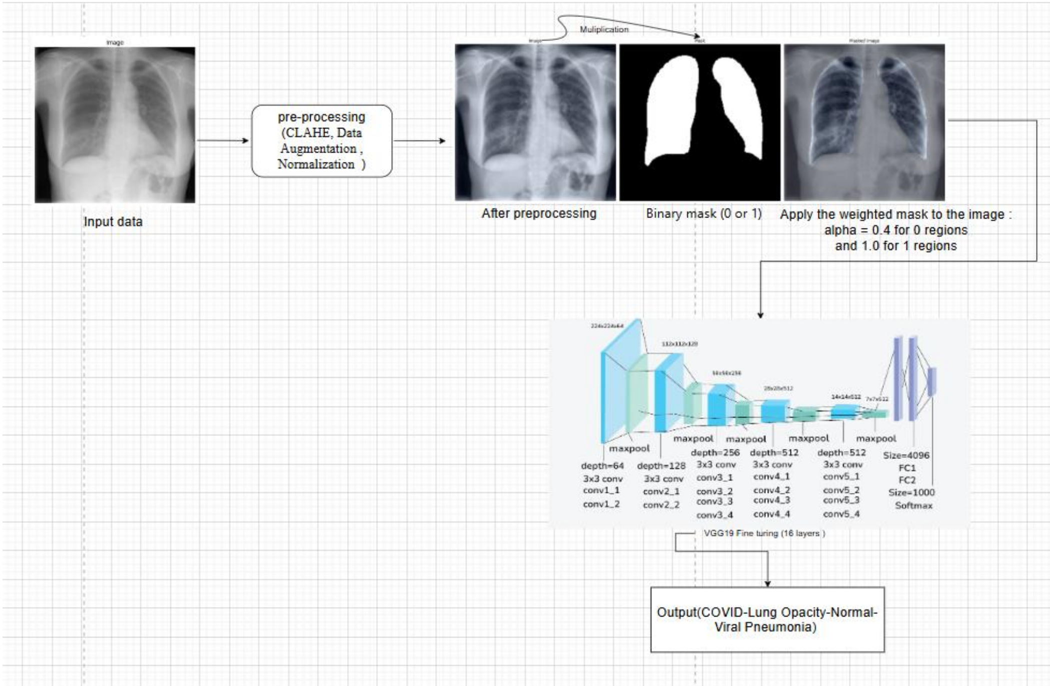

Fig. 6. The framework of the used methodology for Chest X-ray image classification.

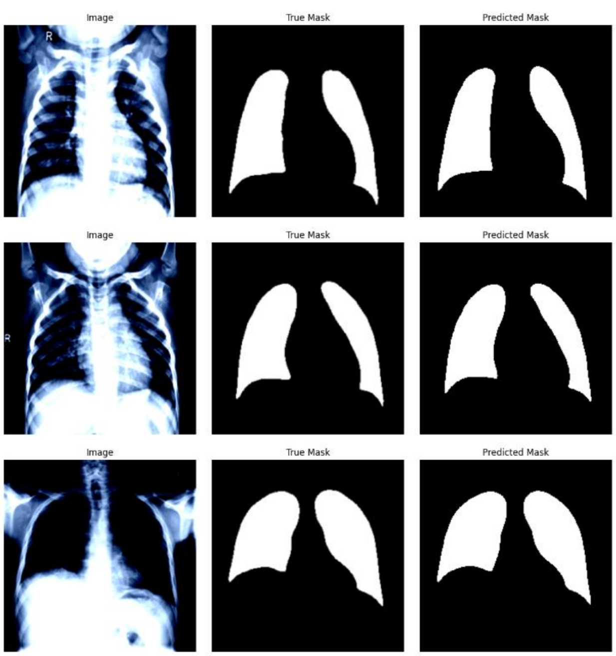

Fig. 7. U-Net was implemented to generate masks.

IV. Performance Metrics and Results

This section discusses the results of models using different evaluation measures.

A. Evaluation Criteria

Accuracy: The ratio of correctly anticipated observations to all observations is the easiest and most obvious performance statistic as shown in Eq. (4). Given in the equation below:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \tag{4}$$

In these formulas:

TP (True Positives) represents the number of correctly predicted positive instances.

TN (True Negatives) represents the number of correctly predicted negative instances.

FP (False Positives) represents the number of negative instances that were incorrectly predicted as positive.

FN (False Negatives) represents the number of positive instances that were incorrectly predicted as negative.

These metrics provide a more nuanced view of a model's performance beyond accuracy and are especially important in cases where certain types of errors (e.g., false positives or false negatives) have different consequences or costs.

Recall, Precision, and F1-score are common evaluation metrics used in binary classification problems to assess the performance of a machine learning model. They are derived from the confusion matrix, which summarizes the model's predictions in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

Here are the formulas for Recall, Precision, and F1-score:

Recall (Sensitivity or True Positive Rate):

Recall measures the ability of a model to identify all relevant instances (true positives) out of all actual positive instances. Eq. (5) shown the Recall or Sensitivity of result.

Formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{5}$$

Precision (Positive Predictive Value):

Precision measures the accuracy of the model's positive predictions and answers the question: "Of all the instances predicted as positive, how many were positive?" Eq. (6) shown the Prevision of data.

Formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{6}$$

F1-score:

The F1-score is a harmonic mean of Recall and Precision. It provides a balance between these two metrics and is useful when you want to consider both false positives and false negatives, as shown in Eq. (7).

Formula:

$$\text{F1 score} = \frac{2\times\text{Recall}\times\text{Precision}}{\text{Recall+Precision}} \tag{7}$$

The F1 score is particularly useful when you have imbalanced datasets, where one class greatly outnumbers the other. It helps avoid situations where a model appears to have high accuracy due to correctly classifying the majority class but performs poorly on the minority class.

The experimental achieved exceptional results, confirming the effectiveness of the methodology that shown in Table I:

TABLE I. EVALUATION MEASURES OF THE MODELS

Model	Precision (%)	Recall (%)	F1-score (%)	Support
COVID	0.98	0.96	0.97	543
Lung Opacity	0.93	0.93	0.93	902
Normal	0.95	0.96	0.95	1529
Viral Pneumonia	0.98	0.97	0.98	202
Accuracy			**0.95**	3176
macro avg	0.96	0.95	**0.96**	3176
Weighted avg	0.95	0.95	**0.95**	3176

A classification model's performance across four classes—COVID-19, lung opacity, normal, and viral pneumonia—is assessed using the image's confusion matrix. The actual class (True) is shown in each row, and the anticipated class is shown in each column. shown in Fig. 8.

Generalization: Consistent training and validation loss/accuracy curves demonstrate minimal overfitting as shown in Fig. 9.

The research demonstrates that combining image segmentation techniques with attention mechanisms and model fine-tuning leads to improved classification of radiographic images. This approach proves valuable in clinical healthcare settings, as it achieves high prediction accuracy while also identifying medically significant features within the images.

When using the model without the mask:

Our study focused on the performance of pre-trained convolutional neural network (CNN) architectures after they were fine-tuned for particular classification objectives. The job involved four classes. Every model configuration included a basic base model that was enhanced by extra layers that were specially designed to meet the particular requirements of the task at hand VGG19 and ResNet101 models were used in our investigation for the 4-class classification scenario. The classification tests were ResNet101 and VGG19. All models received uniform extra layers that were customized to fit each model's architecture.

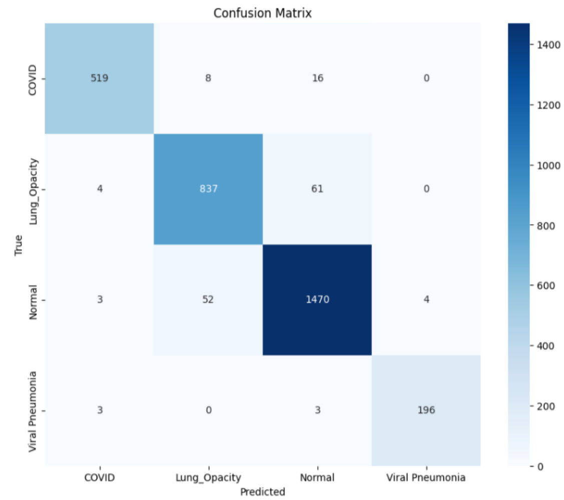

Fig. 8. Classification model's performance.

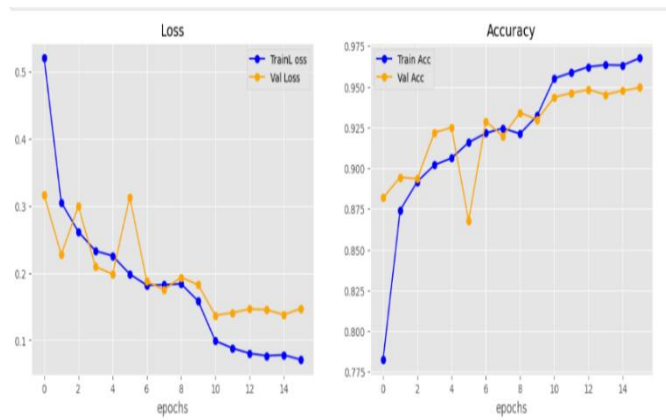

Fig. 9. Loss and accuracy for training and validation over several epochs.

TABLE II. EVALUATION MEASURES OF THE MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
VGG19	94.85	96.25	94.5	95.25
ResNet101	94.28	96	94.25	95

Table II, compares the performance metrics of two popular convolutional neural network models: VGG19 and ResNet101. VGG19 slightly outperforms ResNet101 across all metrics, with an accuracy of 94.85% versus 94.28%. However, the differences are quite minimal, with both models achieving very high-performance scores above 94% across all measures. Looking at these metrics, VGG19 shows a marginal advantage of about 0.25-0.57 percentage points across different measures, though in practical applications this difference might be negligible depending on the specific use case. Fig. 10 and Fig. 11 show the Confusion Matrices of this model.

Fig. 10. VGG19 Confusion matrices.

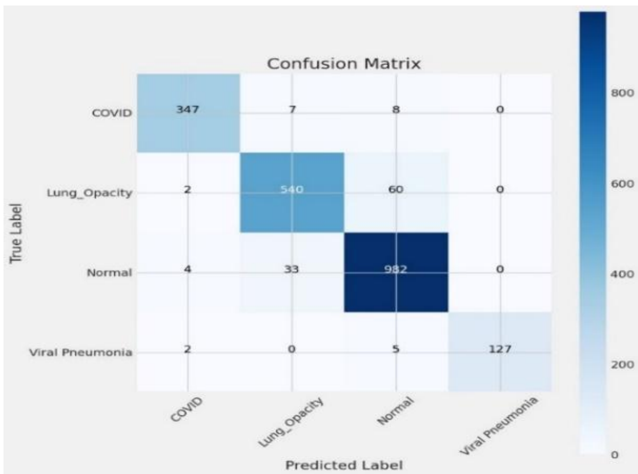

Fig. 11. ResNet101 Confusion matrices.

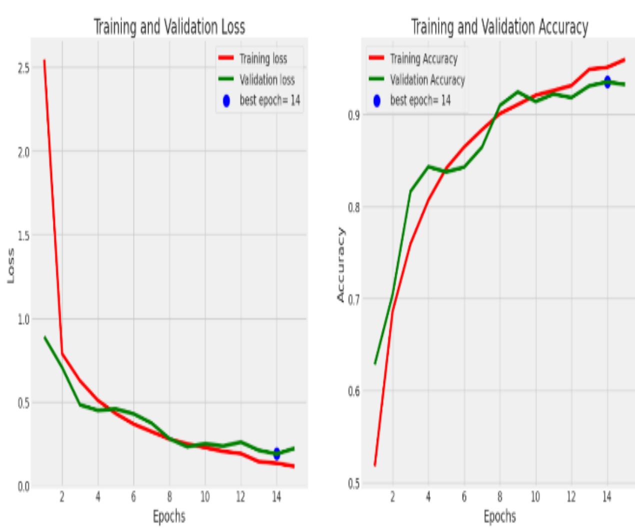

Fig. 12. Loss and accuracy for training and validation over several epochs for the resnet101model.

Fig. 12, shows two graphs side by side, illustrating the performance of a machine learning model during the training and validation phases. Let me break down each graph for you:

1) Left graph - training and validation loss: The horizontal axis displays epochs, which represent complete passes through the dataset. The vertical axis indicates the loss values, where lower values indicate better performance. Training loss (red) and validation loss (blue) both demonstrate a rapid initial decline before plateauing. Throughout the training process, validation loss maintains a slightly elevated position compared to training loss.

2) Right graph - training and validation accuracy: Similar to the loss graph, epochs are shown on the horizontal axis, while accuracy values range from 0 to 1 on the vertical axis. The training accuracy (red) and validation accuracy (green) lines show swift improvement early on before leveling off. Training accuracy consistently outperforms validation accuracy by a small margin.

3) Notable findings: The model demonstrates rapid improvement during the initial epochs for both metrics. A small, consistent gap exists between training and validation metrics, which is typical. Performance improvements become minimal after epochs 14-22, suggesting convergence. The relatively parallel trajectories of training and validation metrics indicate proper model fitting, without significant overfitting concerns.

This visualization helps in understanding how well the model is learning and generalizing to unseen data over time. It can be used to determine the optimal number of training epochs and to check for potential overfitting or underfitting issues.

Our comparative analysis against established models, which primarily used training and testing data splits for validation, demonstrated superior performance of our model, as shown in Table III.

TABLE III. COMPARISON OF THE MODEL'S OBTAINED RESULTS WERE COMPARED WITH THOSE OF OTHER PROPOSED MODELS

Study	Model architecture	Accuracy (in %)
El Houby, E. M. [12]	VGG19	93.5
Our Model	VGG19	**95.0**

Here we have proven that using the mask with the image and making Attention Mechanism the mask work is much better and more accurate than using the normal x-ray image the opposite of what this paper says [12].

V. CONCLUSION AND FUTURE WORK

This Paper proved successful in developing an accurate COVID-19 chest X-ray classification system by combining multiple sophisticated techniques. The approach utilized VGG19 fine-tuning, attention mechanisms, and image segmentation. Image quality was enhanced through CLAHE processing, while data augmentation techniques improved the model's ability to handle diverse cases. The attention component helped the model identify crucial areas in X-ray images, particularly benefiting the detection of COVID-19 and Viral Pneumonia cases. By adjusting class weights and optimizing 16 layers of VGG19 specifically for X-ray analysis, the model achieved 95% validation accuracy and a 96% macro-average

F1-score. The integration of Probabilistic U-Net for segmentation helped isolate lung regions and reduce interference from surrounding areas, leading to more accurate predictions.

The model demonstrated strong performance metrics across all categories with balanced precision and recall scores. The similar trajectories of training and validation metrics indicated good generalization without overfitting, suggesting the model's readiness for clinical application.

Looking ahead, researchers plan several enhancements: expanding the training data for better generalization, improving segmentation through advanced networks like Attention U-Net and DeepLabV3+, and incorporating additional imaging modalities such as CT and MRI scans. The team also aims to implement interpretability tools like Grad-CAM and SHAP to make the model's decisions more transparent to healthcare providers. Future developments will explore mobile and cloud deployment options, with additional validation using external datasets to ensure reliable performance in clinical settings. These improvements aim to create a dependable automated system for detecting and diagnosing respiratory conditions early.

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