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COVID-19 Detection from X-Rays Using CNN

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Introduction: COVID-19 broke out in December 2019 and was recognized by the World Health Organization (WHO). It spread to approximately 114 countries worldwide, with the first reported case identified in China. The initial diagnostic technique for detecting COVID-19 was reverse transcription polymerase chain reaction (RT-PCR). Artificial intelligence and deep learning have revolutionized healthcare by enhancing the accuracy, speed, and accessibility of diagnosis. As a result, researchers are actively working on the early detection of COVID-19.

Novelty: Preprocessing is a critical step in feature extraction in image processing. While existing studies used the fractal technique, our research employs the moving filter technique for the feature extraction. The main advantage of our method over the existing technique is its ability to capture the local spatial variation rather than the global self-similarities. Additionally, a local dataset sample was collected from a local hospital to evaluate the performance of the trained model. The model is trained on a labelled dataset, which is collected from Kaggle, and a local labelled dataset is used to assess its prediction performance for COVID-19 detection.

Material and Methodology: This study proposes a deep learning-based classification model using a Convolutional Neural Network (CNN) for the diagnosis of COVID-19. The model enables rapid disease detection by capturing the fine-grained details at the pixel level from the chest x-ray images. It was trained on a dataset consisting of two classes: 4,641 COVID-19 images and 4,641 normal images. Data augmentation was also applied to enhance the diversity of the dataset. The performance of the proposed model was compared with the five existing models, taking into account the number of layers used for feature detection in chest X-ray images.

Results and Discussion: The proposed model consists of 8 layers for extracting abnormalities from the chest X-ray images. It was trained over 150 epochs on a dataset of 8,762 samples, achieving an overall accuracy of 92.31%, precision of 95%, recall of 89%, and F1-score of 92%. However, when the dataset size could not be increased, and the number of epochs was raised, the resulting improvements in accuracy and precision were negligible. This indicates that the model achieves optimal performance with fewer epochs, requiring less training time and computational resources compared to the other approaches.

Conclusion: The proposed CNN model achieved a high accuracy of approximately 93% on the test dataset, demonstrating its effectiveness through strong generalization on unseen data and consistent performance across both classes. This indicates that the model can reliably distinguish between COVID19 and normal chest X-ray images. These results suggest that the approach can support an automated diagnostic system.

Keywords: Deep Learning, Convolutional Neural Network, Chest X-rays, Artificial Intelligence.

Introduction:

In December 2019, an unknown virus broke out in the city of Wuhan, China [1]. People began falling ill with a disease that was initially unfamiliar to doctors. In early January 2020, the World Health Organization officially recognized the virus as coronavirus [2]. The infection spread rapidly within China and to other countries, affecting both developing and developed nations around the world [3]. Researchers have reported that COVID-19 primarily affects the respiratory system, with common symptoms including dry cough, fever, fatigue, and loss of sense of taste [2]. The United States was among the most affected countries, with 39,63,376 confirmed cases and 1,43,889 deaths reported as of 21 July 2020 [4]. Initially, the virus affected animals, then transmitted from animals to humans and subsequently spread between humans through person-to-person contact. University College London first recognized these common symptoms associated with the virus, including fever, cough, headache and breathlessness [4].

The primary technique for testing COVID-19 in affected individuals is the reverse transcriptase real-time fluorescence polymerase chain reaction (RT-PCR). However, this method is time-consuming, and the accuracy ranges from approximately 30% to 60% [5]. This approach has several limitations, including a lengthy process and a higher likelihood of false positive results, which can increase patient stress [6]. Additionally, RT-PCR requires specialized laboratory equipment, and limited resources, particularly in rural areas, may delay proper diagnosis and treatment [7]. An alternative approach is the use of deep learning-based methods. One approach is to build a high-performance model by using the pretrained network, while another is to train a model from scratch; both have their advantages and disadvantages. Transfer learning is often employed to achieve high performance, as the pre-trained model has already learned similar features, allowing training with less data and reducing time [7]. However, a key limitation of pre-trained models is that features learned from general images differ from medical imaging features, which can limit their effectiveness in disease diagnosis [8].

In this study, the model is trained from scratch, providing full control over the network architecture and enabling it to learn directly from the target dataset without relying on pre-learned biases. In contrast, pretrained models offer limited flexibility in architecture design and typically require extensive fine-tuning to adapt to domain-specific data. The proposed model is evaluated using a non-pretrained convolutional neural network for binary classification, distinguishing between COVID-19 positive and normal cases, while considering dataset characteristics, memory constraints, and computational resources. The architecture employs a reduced number of layers, thereby minimizing memory consumption and computational resources. Furthermore, for the real-time prediction evaluation, a locally collected dataset was utilized, whereas the training and testing datasets were obtained from Kaggle. Since the Kaggle dataset does not include samples from Pakistani patients, the local dataset specifically represents the Pakistani population to enhance regional relevance and model applicability.

Research Objectives:

The primary research objective of this study is to develop an efficient and lightweight deep learning model for the accurate detection of COVID-19 from chest X-ray images. To achieve this goal, the study focuses on the following specific and measurable objectives:

To design and implement a convolutional neural network (CNN) architecture trained from scratch, enabling full control over feature learning without reliance on pre-trained models.

To evaluate the performance of the proposed model using standard classification metrics, including accuracy, precision, recall, and F1-Score, for a reliable assessment of diagnostic capability.

To minimize computational complexity by employing a reduced number of layers, thereby lowering memory usage and training time while maintaining high performance.

To compare the effectiveness of a non-pre-trained model against existing deep learning approaches that utilize transfer learning

To assess model generalizability using a publicly available dataset (Kaggle) and a locally collected dataset representing the Pakistani population.

Novelty of the Study:

This study introduces a novel approach for COVID-19 detection from chest X-ray images by developing a convolutional neural network trained entirely from scratch, enabling full control over the model architecture and eliminating dependency on pre-trained weights. Unlike conventional transfer learning methods, the proposed approach allows the model to learn task-specific features directly from the dataset without inheriting biases from general-purpose image datasets. In addition, the proposed model employs a reduced number of layers, resulting in a lightweight architecture that minimizes memory usage and computational cost while maintaining effective performance. This makes the model more suitable for deployment in resource-constrained environments.

Furthermore, a unique aspect of this study is the use of a locally collected dataset representing the Pakistani population for real-time prediction, alongside a publicly available Kaggle dataset used for training and testing. Since existing datasets lack regional diversity, the inclusion of local data enhances the model's practical applicability and relevance in real-world healthcare settings.

Related Work:

Many deep learning approaches have demonstrated empirical results in diagnosing disease, particularly using pre-trained models, such as [9] presented the COVIDX-Net model to assist the radiologist for the automatic detection of COVID-19. In the preprocessing stage, the images were rescaled to a size of 224*224 pixels, and one-hot encoding was applied. The dataset was divided into training and testing subsets, with 80% used for training and 20% testing. [10] Proposed the DarkCovidNet model, which has been employed in remote areas of various countries to address the shortage of radiologists. The author did not use any feature extraction techniques and trained the model using 17 convolutional layers, followed by the batch normalization layer and LeakyRelu layer activation functions.

Sousa et al. proposed the CNN model for the detection of COVID-19. Chest X-ray images [11]. The goal was to identify anomalies at the early stage [11]. The authors used two datasets: Dataset I, consisting of 434 images, and Dataset II, consisting of 4,030 images. Due to the limited size of the dataset of Dataset I, data augmentation was performed. However, since the second dataset was sufficiently large, data augmentation was not applied to it. The following techniques were used for data augmentation: range rotation, width shift range, height shift range, zoom range, horizontal flip, and vertical flip. The model employed convolutional and pooling layers for classification, with adaptive moment estimation (ADAM) used as an optimizer. A sigmoid activation function was used for the classification task. Using a batch size of 20 and training for 500 epochs, the model achieved an average accuracy of 97.22%, a recall of 98.83%, and a specificity of 97% across both datasets.

[12] Uses chest X-ray images to train the model for the classification of COVID-19. The dataset consisted of 2,875 COVID-19 infected images, 3,218 normal images, and 4,200 pneumonia chest X-ray images. The model architecture consisted of five convolutional blocks, with each block consisting of an activation function, specifically the ReLU activation function. The third and fourth blocks included a dropout layer to reduce overfitting. The model also featured two fully connected layers: the first with a dropout layer, and the second with a Softmax function for classification. The model was trained using a batch size of 32 and 25 epochs with the ADAM optimizer. The performance metrics for the COVID-19, Normal, and

Pneumonia classification were as follows: accuracy values were 96.3%, 99.2%, and 95.9% respectively, sensitivity 93%, 99%, and 96% respectively, specificity 97.4%, 99.3%, and 94.9% respectively, precision 92%, 92%, and 98% respectively, and F1-Score 92%, 95%, and 97% respectively.

[13] Developed the OptCoNet model, utilizing Grey Wolf Optimizer (GWO) for the feature extraction. The dataset consisted of three classes: 1000 COVID-19 images, 900 Normal images, and 900 Pneumonia images. The model architecture included one input layer, five convolutional layers, four max-pooling layers, one fully connected layer, and one output layer. The model was fine-tuned using Stochastic Gradient Descent (SGD) for 10 epochs. The following results were achieved: accuracy, sensitivity, specificity, precision, and F1-Score are 97.78%, 97.75%, 96.25%, 92.88%, and 95.25%, respectively.

[14] Developed a convolutional neural network model applied directly to chest X-ray images. The model consists of 16 layers, four of which are convolutional. It was trained for 400 epochs. The results achieved are as follows: accuracy 93.2% and sensitivity 96.1%.

Similar to other studies, [15] developed a deep learning-based convolutional neural network using a dataset consisting of 504 chest X-ray images, 362 normal chest X-ray images, and 866 pneumonia images. Due to the small dataset size, data augmentation was performed to increase the diversity of the data across all three classes. The following five techniques were applied for data augmentation: shearing, horizontal flip, zooming, brightness increase, and brightness decrease. After this, the model was trained using 23 layers, including 11 convolutional layers, 4 max-pooling layers, 5 dropout layers, and 2 dense layers. The model was trained for 50 epochs and achieved the following results: 97.67% accuracy, 95.2 precision, 1 recall, and 95.7% F1-score.

Most studies represent 97% accuracy and 96% precision when using deeper neural network models with additional layers and dropout layers. While adding more layers allows the model to learn more complex features, it also increases the model's complexity, making hyperparameter tuning more challenging. Training such models requires significantly more computational power and memory. Moreover, training often involves more epochs. Moreover, there is an increasing need for hyperparameter tuning. This process is time-consuming and costly due to the high demand for computational resources.

Materials and Methods:

Proposed Methodology:

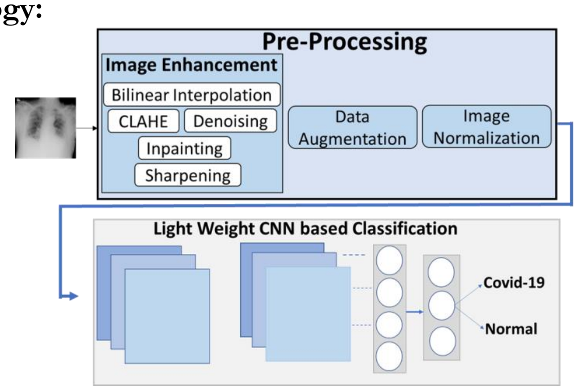

Figure 1. Block Diagram of Proposed Methodology

The proposed methodology was developed to classify the COVID-19-infected and normal chest X-ray images, as illustrated in Figure 1. This complete workflow consists of two major stages: 1. Pre-processing and 2. Classification using a lightweight CNN model. In the first stage, raw chest X-ray images are enhanced through bilinear interpolation, CLAHE, denoising, inpainting, and sharpening to improve the image quality. To increase dataset diversity and reduce overfitting, data augmentation techniques, including rescaling, rotation, width shift, height shift, shear, zoom, and flipping, are applied. The enhanced image was normalized by scaling pixel intensity values to ensure stable and efficient model training. In the second stage, the preprocessed images were passed to the proposed lightweight convolutional neural network, where convolution, batch normalization, pooling, and fully connected layers were used to extract features and perform binary classification into COVID-19 and Normal classes [2]. The detailed explanation of each component is presented in the following subsections.

Dataset Used:

In this research, publicly available chest X-ray datasets were obtained from Kaggle, using the link https://www.kaggle.com/tawsifurrahman/datasets. The Kaggle dataset was selected because it provides a large number of labeled COVID-19 and normal chest X-ray images, making it suitable for supervised deep learning experiments. In addition, publicly available datasets enable reproducibility and comparison with previous studies. The original dataset consisted of 3,616 COVID-19 images and 10,192 normal chest X-ray images. To avoid class imbalance during training, a balanced subset of 3,616 COVID-19 X-ray images and 3,616 normal chest X-ray images was selected.

To evaluate the real-world applicability, an additional local hospital dataset was collected, consisting of 1,000 chest X-ray images, including 500 COVID-19 positive and 500 normal cases. The hospital dataset was incorporated to assess model generalization on data representing the Pakistani population, which is underrepresented in publicly available datasets. Table 1 provides a summary of the dataset, while Figure 2 illustrates the sample COVID-19 and Normal chest X-ray images.

Inclusion Criteria:

The following images were included in this study:

Frontal chest X-ray images with acceptable image quality.

Clearly labeled COVID-19 positive and normal cases.

Images compatible with preprocessing and CNN dimensions.

Exclusion Criteria:

Duplicated images.

Blurred and low-quality radiographs.

Ethical Considerations:

For the hospital dataset, all patient-identifiable information was removed before analysis to ensure privacy and confidentiality. The dataset was used solely for research purposes in compliance with institutional data protection policies. Where required, approval was obtained from the relevant hospital or institutional authority before data usage.

Table 1. Description of the dataset

Number of Chest X-ray Images			
Dataset	**Covid-19**	**Normal**	**Total**
Dataset 1	3616	3616	7232
Dataset 2	1000	1000	2000
Dataset 3	500	500	1000

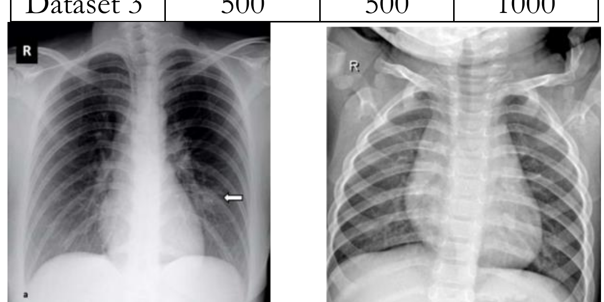

Figure 2. Frontal view CXR samples of two categories (a) COVID-19, (b) Normal

Preprocessing:

This stage is critical in the proposed approach, as it cleans and transforms the raw data for the analysis, ensuring that the model can learn effectively and achieve more accurate predictions. Additionally, it helps reduce the training time [16].

Image Enhancement is the process of reducing redundancy and improving the quality of an image**.** This includes removing noise and highlighting fine details at the pixel level. Image enhancement techniques can be broadly categorized into two main approaches:

Spatial domain method

Frequency domain method.

In this study, the Spatial domain method is employed, as frequency analysis is not required for the intended image processing tasks [17]. Within the spatial domain, bilinear interpolation is used to enhance the image quality by adjusting the intensity values of pixels [18][2]. Following bilinear interpolation, additional enhancement techniques are applied, including contrast-limited adaptive histogram equalization (CALHE), Denoising, Inpainting, and Sharpening.

Image enhancement consists of the following steps.

Bilinear Interpolation

Contrast Limited Adoptive Histogram Equalization

Denoising

Inpainting

Sharpening

The preprocessing techniques were selected based on their effectiveness in enhancing chest X-ray image quality while maintaining computational efficiency. Bilinear interpolation was chosen for its balance between simplicity and smooth intensity transitions. CLAHE was preferred over global histogram equalization as it enhances local contrast while limiting noise amplification [19]. A patch-based denoising approach was used instead of conventional filters to preserve fine structural details critical for diagnosis, as noise can significantly degrade medical image quality [20]. Inpainting was incorporated to restore corrupted regions, improving structural consistency. Finally, sharpening enhances edge details and feature visibility. Overall, preprocessing techniques such as CLAHE and denoising have been shown to improve CNN-based classification performance in chest X-ray analysis [21].

Bilinear Interpolation is used to resize the image by calculating the weighted average of the four nearest neighboring pixels.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to enhance the contrast of an image by dividing it into small regions and performing local histogram equalization [2]. The histogram of each tile is calculated, redistributing pixel intensities to achieve a uniform histogram and locally enhanced contrast. A cumulative distribution function is then computed and mapped to the existing pixel value. A major drawback of adaptive histogram equalization is the potential for over- amplification of noise; CLAHE addresses this by applying a clip limit, ensuring no pixel value exceeds the specified threshold and reducing noise amplification.

Denoising is used to remove noise from images, particularly in low-light conditions, and to restore the original image [22]. The process begins by considering each pixel in the image and calculating the similarity distribution from the Euclidean distance. Similar patches are then identified, and a weighted average of the surrounding pixels is computed. Patches that are more similar to the target patch contribute more to the weighted average, while less similar patches contribute less. Finally, the computed weighted average pixel is assigned to the target pixel [23].

Inpainting is used to fill in the missing pixel values or damaged parts of the image by referencing the neighboring pixels [24]. In this research, a patch-based approach is employed to restore the missing pixel values. First, the damaged region of the image is identified. Similar patches to the damage areas are then located, and a similarity metric is calculated using the sum of squared differences. The patch with the highest similarity to the target region is selected. Through a weight aggregation process, higher weights are assigned to patches that are more similar to the missing region. Finally, the aggregated patch is used to fill the missing pixels.[24].

Sharpening, which is used to enhance the edges and fine details of the image [25]. By applying all these processing techniques, bilinear interpolation, CLAHE, denoising, inpainting, and sharpening, the overall image quality is improved in terms of sharpness, contrast, and visual clarity. The outcome of the image enhancement stage is illustrated in Figure 3.

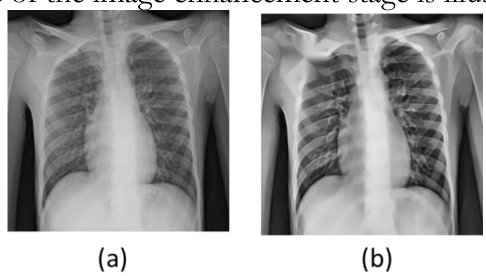

Figure 3. Frontal view of (a) Normal, (b) Enhanced image.

Data Augmentation is a deep learning technique used to generate artificial data from existing datasets. Convolutional Neural Networks typically underperform on small datasets, so training on a large dataset helps improve performance. Additionally, the data augmentation acts as a regularizer, reducing the risk of overfitting [26]. In this study, data augmentation was applied during training using six techniques: rescaling, rotation, width shift, height shift, shear range, zoom range, horizontal flip, and vertical flip. Two new images were generated for each augmentation technique, increasing the diversity of the training dataset.

Image Normalization Data normalization is an important step to ensure the input pixel has a similar distribution, which accelerates convergence during model training. Each pixel is normalized by multiplying it by 1/255 so that the mean and standard deviation of the image are approximately 0.0 and 1.0, respectively. This normalization step helps preserve numerical stability in the CNN model [2].

CNN Model:

Deep learning has the potential to revolutionize healthcare due to its self-learning capabilities. It can capture the fine-grained details and provide accurate results in a minimal time; however, training deep models is often computationally expensive and memory-intensive [15]. Therefore, there is a need for a lightweight neural network that requires less cost and memory while maintaining high performance in both binary and multiclass classification. CNN models generally provide strong performance in both binary and multi-class classification problems. The proposed architecture consists of 8 layers, with the detailed configuration of the model in **Error! Reference source not found.** This model uses chest X-ray images for classification.

The proposed lightweight CNN architecture is specifically designed to improve COVID-19 detection performance while reducing computational complexity compared with existing deep and transfer learning-based models. Unlike pre-trained networks that contain millions of parameters and require extensive fine-tuning, the proposed model employs a compact architecture with only essential convolutional, pooling, and dense layers for efficient feature extraction. This reduces memory consumption, training time, and risk of overfitting on a limited medical dataset. In addition, the integration of an enhanced preprocessing pipeline, including contrast enhancement, denoising, inpainting, and sharpening, improves the visibility of infection-related patterns in chest X-ray images. These improvements enable the model to achieve accurate and reliable classification of COVID-19 and normal cases at lower computational cost, making it more practical for real-time clinical deployment and resource-constrained healthcare environments.

Table 2. Detailed Configuration of the proposed model

Layer	Feature maps	Parameters	Kernel size
Input	1	-	-
Convolutional	62	620	(3,3)
Batch normalization	62	248	-
Max pooling	62	0	(2,2)
Convolutional	32	17888	(3,3)
Batch normalization	32	128	-
Max pooling	-	0	-
Flatten	-	0	-
Dense	-	170529	-

Convolutional Layer:

The input image is represented as a matrix and passed to a convolutional layer, which is responsible for extracting features such as edges. patterns, and texture [9]. Each filter (kernel) acts as a feature detector and requires several hyperparameters, including the number of filters, filter size, padding size, and stride [2].

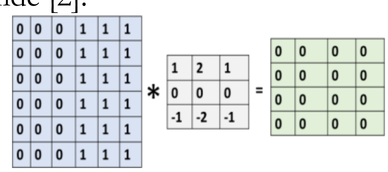

Figure 4. Convolutional Operation [17]

This layer consists of multiple filters, where each filter is convolved against the input to generate a corresponding feature map [27]. The convolutional operation, illustrated in Figure 4, involves multiplying each element of the filter by the corresponding local region of the input image and then summing the results. As the filter moves across the image, it captures the meaningful patterns and features [17]. In this methodology, a filter size of 3*3 is used with a stride size of 1. The size of the output feature map is calculated using the following equation:

$$Output\ size = \frac{n - f + 2p}{S}$$

Where n represents the size of the input image, f is the filter (kernel) size, p denotes the padding applied to the input, and "S" is the stride of the convolution. The floor operation ensures that the output size is an integer. The formulation provides a generalized computation of the feature map size, accounting for different convolution settings.

Batch Normalization Layer:

When the input data is unstable or unnormalized, the training process becomes slower. Batch normalization is a technique used to accelerate training by normalizing the activation values produced by the preceding layer. Normalization ensures that the activations have means 0 and standard deviation 1. This technique is applied to the hidden layers during the training and is performed on mini-batches rather than the entire dataset [28]. Batch Normalization also acts as a regularizer, helping to reduce overfitting. It is typically placed between the convolutional layer and the ReLU layer [2]. Figure 5 illustrates how batch normalization is applied in a feed-forward neural network.

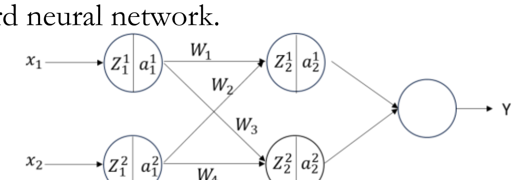

Figure 5. Forward feed neural network [28]

Where:

x_i = *input of the neurons*

Z_i = *activation function is applied*

a_i = *output of the neuron*

Y = *output of the network*

ReLU Layer:

This layer plays an important role in introducing non-linearity into the network, enabling it to learn complex patterns [9]. The Rectified Linear Unit (ReLU) activation function is commonly used due to its computational efficiency. ReLU outputs zero for any negative input, and for zero or positive inputs, it returns the input value unchanged [2]. Figure 6 demonstrates the behavior of the ReLU function when negative inputs are applied.

$$\begin{bmatrix} 1 & -3 & 2 \\ -2 & 0 & 4 \\ 1 & -2 & -2 \end{bmatrix} \xrightarrow{\text{ReLU}} \begin{bmatrix} 1 & 0 & 2 \\ 0 & 0 & 4 \\ 1 & 0 & 0 \end{bmatrix}$$

Figure 6. ReLU on 3*3 matrix:

ReLU function can be represented by mathematical ReLU=max(0,υ) [29].

Pooling Layer:

Pooling is used to down sample the spatial dimensions of the image by reducing redundant or insignificant features, making the representation more compact and interpretable [16]. It helps the network learn invariant features and also functions as a regularizer, thereby reducing the risk of overfitting. Additionally, pooling significantly lowers computational cost and training time, which is an essential consideration in deep learning models. In this work, max pooling is used [29]. Generally, pooling is of two types: max-pooling and average-pooling. In our model, a max-pooling layer with a 2 * 2 kernel is applied after batch normalization.

$$\begin{bmatrix} 8 & 3 & 5 & 9 \\ 4 & 7 & 3 & 6 \\ 1 & 9 & 2 & 5 \\ 2 & 6 & 1 & 4 \end{bmatrix} \longrightarrow \begin{bmatrix} 8 & 9 \\ 9 & 5 \end{bmatrix}$$

Figure 7 illustrates the max-pooling operation.

$$\begin{bmatrix} 8 & 3 & 5 & 9 \\ 4 & 7 & 3 & 6 \\ 1 & 9 & 2 & 5 \\ 2 & 6 & 1 & 4 \end{bmatrix} \longrightarrow \begin{bmatrix} 8 & 9 \\ 9 & 5 \end{bmatrix}$$

Figure 7. Max- pooling operation [17]

The input image is divided into rectangular partitions and then the maximum value is selected from each rectangular partition [17]. The function of the pooling is

MaxPooling(F, W)=max(W)[2]

Here

F = input feature map

W = window pooling

Fully Connected layer:

The fully connected (FC) layer is the final stage of the convolutional neural network. In this layer, each neuron is connected to every neuron in the previous layer, which is why it is referred to as a fully connected layer. Before entering the FC layer, the output feature maps are flattened from a 2D matrix into a 1D [9]. This flattening operation converts the spatial feature representations learned in the earlier layer into a single-dimensional array. Moreover, it serves as a bridge between extracted features and the classification task. By combining and weighting these important features, it makes the final decision regarding the class to which the input image belongs.

Results and Discussion:

Experimental Setup and Results:

This model was trained using the three datasets. The first dataset consists of 3616 COVID-19 and 3616 normal chest X-ray images. The second dataset consists of 1000 COVID-19 and 1000 normal images, while the third dataset was collected from the hospital and includes 1000 images for each class. This model was developed using the Tensor Flow framework, and all experiments were conducted on Google Colab. For training. 80% of the data was used, whereas the remaining 20% was reserved for testing. To increase the data diversity and reduce overfitting, data augmentation was applied using hyperparameters listed in Table 3:

Table 3. Illustration of the hyperparameters of data augmentation

Parameters	Values
Rotation Range	20
Width Shift Range	20%
Height Shift Range	20%
Shear Range	20%
Zoom Range	20%
Horizontal Flip	20%

The performance of the model was evaluated using standard metrics such as accuracy, precision, recall, and F1-Score. The hyperparameters of the model are represented in *Table* **4**:

Table 4. Illustration of the hyperparameters of the model

Hyper-parameters	Values
Batch Size	32, 64
Learning Rate	0.01, 0.001, 0.0001
Epochs	150, 200, 250
Optimizers	Gradient Descent
Loss function	Binary cross-entropy

Results of the Proposed Model:

The proposed model convolutional neural network was trained using different sets of hyperparameters, including the number of iterations, batch size, learning rate, and the number of layers. Multiple models were trained by varying these parameters, enabling a comparative analysis of their performance. Through this iterative process, an optimized CNN architecture was obtained for accurate classification.

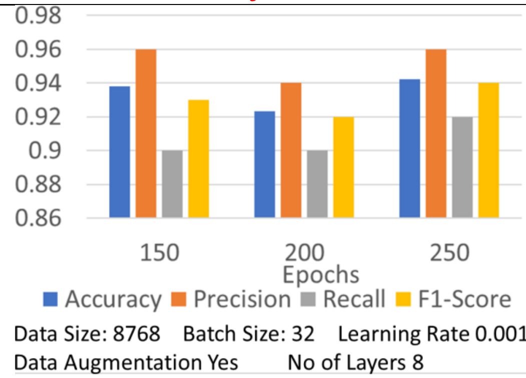

Figure 8. Effect of Number of Epochs on Model Performance

Figure 8 illustrates the impact of training epochs on model performance. It is observed that accuracy, precision, recall, and f1-score improve as the number of epoch's increases, indicating better learning of feature representation. However, beyond an optimal point, performance gains become marginal while the risk of overfitting increases, as the model begins to memorize training data rather than generalize. This observation supports the need for controlled training in lightweight CNNs to balance accuracy and generalization, aligning with the study objective of developing an efficient and reliable classification model.

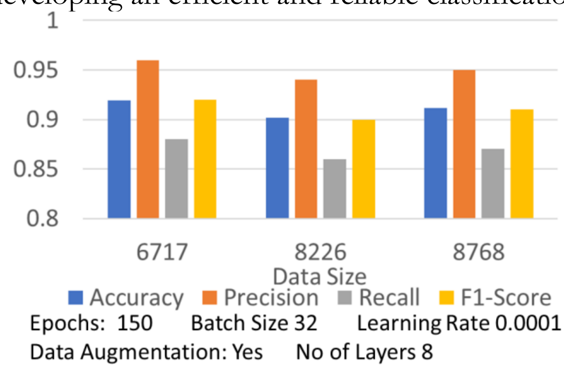

Figure 9. Effect of Data Size on Model Performance

Figure 9 presents the influence of dataset size on model performance. While increasing the dataset size introduces variability and initially causes fluctuations in performance metrics, it ultimately enhances the model's generalization capability. This is particularly important for medical imaging tasks, where robustness to unseen data is critical. These results demonstrate that incorporating a larger and more diverse dataset improves the reliability of the proposed model, supporting its applicability in real-world clinical settings.

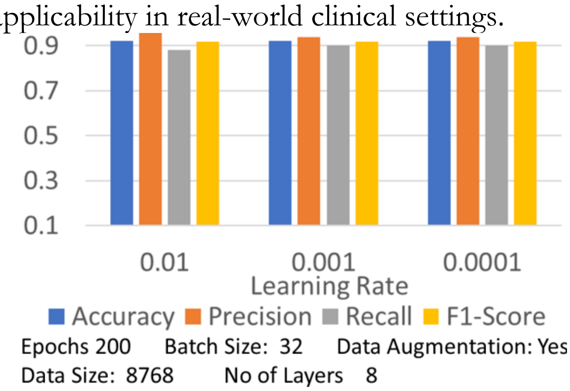

Figure 10. Effect of Learning Rate on Model Performance

Figure 10 shows the effect of different learning rates on model performance. A relatively higher learning rate leads to faster convergence and improved performance within fewer iterations. However, excessively large learning rates may risk overshooting optimal minima, while a very small learning rate slows down convergence. The selected learning rate achieves a balance between convergence speed and stability, contributing to efficient training of a lightweight CNN model.

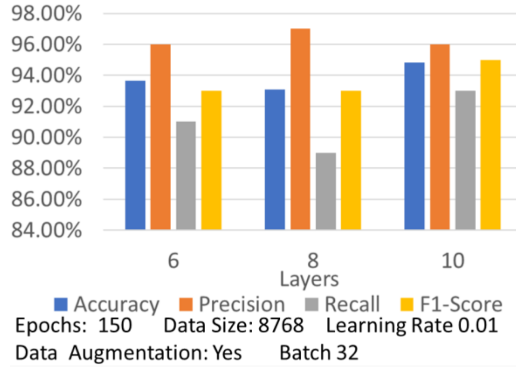

Figure 11. Effect of Number of Layers on Model Performance

Figure 11 demonstrates the impact of network depth on classification performance. Increasing the number of layers allows the model to learn hierarchical feature representations, from low-level edges to high-level patterns associated with COVID-19 infection. However, deeper architectures also increase computational complexity and risk of overfitting. The results indicate that the proposed lightweight architecture achieves an effective trade-off between model complexity and performance, which is essential for deployment in resource-constrained environments.

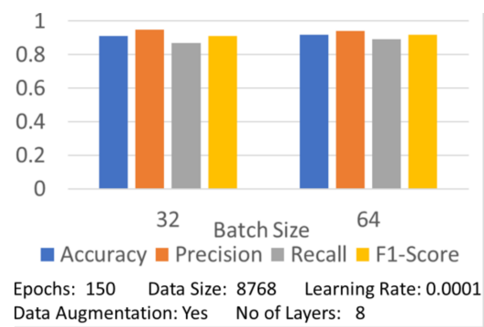

Figure 12. Effect of Batch Size on Model Performance

Figure 12 illustrates the relationship between batch size and model performance. Larger batch size provides more stable gradient estimates, leading to smoother convergence and slightly improved performance. In contrast, a smaller batch size introduces noise in gradient updates, which may hinder convergence but can sometimes improve generalization. The selected batch size ensures stable training while maintaining computational efficiency, aligning with the lightweight design objective of the proposed model. The model's performance was assessed using the confusion metrics, as shown in Figure 13.

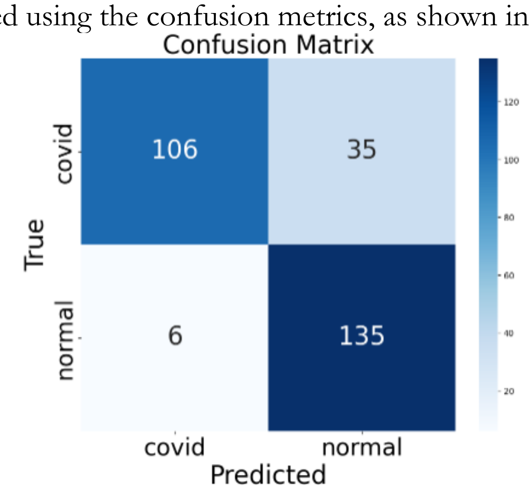

Figure 13. Confusion Matrix

Comparative Analysis with Existing Approach:

The experimental results in **Table 5** demonstrate that the proposed convolutional neural network is effective for COVID-19 classification from chest X-ray images. The model successfully learns discriminative features while reducing irrelevant information, enabling accurate identification of COVID-19 cases. As presented in the results section, the proposed approach achieves high classification performance in terms of accuracy and other evaluation metrics.

The performance of the proposed lightweight CNN model was compared with that of an existing convolutional neural network proposed by [14]. It is important to note that a comparison is challenging due to differences in dataset size, preprocessing techniques, and experimental settings. The model in [14] was trained on a relatively smaller dataset, whereas the proposed model utilizes a larger and more diverse dataset, which improves generalization capability. Despite these differences, the comparison provides useful insights into model efficiency and performance trends. The proposed model achieves competitive results while using fewer layers and reduced computational complexity, leading to lower training time and memory requirements. In contrast, the model [14] employs a deeper architecture with padding and requires more training iterations, increasing computational cost.

Although slight variations in accuracy and sensitivity are observed, the proposed model demonstrates robust performance and better suitability for real-world applications due to its efficiency and ability to generalize across diverse data. This highlights that model evaluation should consider not only accuracy metrics but also dataset scale, computational cost, and practical deployment constraints.

Table 5. Comparison of Proposed CNN

	Existing Model	**Proposed Model**
Objective	To diagnose COVID-19 from a convolutional neural network from a chest CT Scan image.	To diagnose COVID-19 from a convolutional neural network from chest X-ray images.
Methodology	Image classification and detection from CNN.	Image classification and detection from CNN.
Dataset Used	682	8762
Performance of Model	Accuracy, Precision, Recall, F1-Score, Area under the receiver operating characteristic curve (AUC-ROC).	Accuracy, Precision, Recall, F1-Score.
Outcomes	Accuracy 93.2%, Precision 99%, Recall 96.1%, F1-Score 97.97%, AUC-ROC 95%	Accuracy 92.31%, Precision 95%, Recall 89%, and F1 92.
Limitations	Limited dataset, lack of validation in the real environment.	Large dataset validation in the real environment.

Conclusion:

In this study, a lightweight convolutional neural network was developed for the rapid and automated detection of COVID-19 from chest X-ray images, to achieve high classification performance while maintaining low computational complexity for real-time applications. The dataset was split into 80% training and 20% testing, and all images were converted to grayscale and resized to 256*256*1 for uniform processing. The proposed model achieved an accuracy of 92.31%, precision of 95%, recall of 89%, and F1-score of 92%, demonstrating strong and balanced performance for COVID-19 classification. These results confirm that the model effectively learns discriminative radiographic features while maintaining robustness across evaluation metrics. For a practical and clinical perspective, the proposed approach can assist radiologists by providing fast and automated screening of chest X-ray images, particularly in high- demand healthcare environments. Due to its lightweight architecture with only two convolutional layers and reduced computational cost, the model is suitable for deployment in resource-constrained settings such as rural hospitals and primary care centers, where rapid preliminary diagnosis is critical. However, the study has certain limitations. Future work should focus on validating the model on larger and multi-institutional datasets to improve generalization across diverse populations. In addition, integrating the model into real-time clinical decision support systems and comparing it with advanced transfer learning architectures would provide further performance insights. Future improvements may also include optimizing hyperparameters using automated search techniques, evaluating different optimizers, and extending the model for multi-class classification of other lung diseases, such as pneumonia and tuberculosis.

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