Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Detection of respiratory viral infection Through X-Ray Using Convolutional Neural Network

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ABSTRACT

Respiratory infections, caused by various viruses and bacteria, pose a persistent and significant global health challenge. The emergence of the COVID-19 pandemic in December 2019 underscored the vulnerabilities inherent in healthcare systems worldwide. Nonetheless, the fight against COVID-19 has unveiled several challenges, including a scarcity of COVID-19 testing kits and the time-consuming nature of the current gold standard diagnostic technique, Reverse Transcription Polymerase Chain Reaction (RT-PCR). The limitations in testing capacity and the need for more efficient diagnostic methods have spurred innovative approaches, such as using deep learning techniques, to address these issues.This study explores the application of deep learning techniques, specifically a convolutional neural network (CNN), for rapid COVID-19 detection using chest X-ray images. A custom deep CNN model is designed and evaluated for ternary classification of COVID-19, viral pneumonia, and normal cases.

Experimental results demonstrate an average classification accuracy of 91.59% and an F1-score of 92.00%, indicating strong discriminative capability. These findings suggest that the proposed model holds promise as an efficient adjunctive tool for COVID-19 screening, with potential implications for pandemic response, patient triage, and resource allocation. Limitations of the current study, including dataset constraints and the need for prospective clinical validation, are also discussed, along

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with directions for future work involving larger and more diverse imaging datasets.

Keywords: Convolutional Neural Network (CNN), Medical Imaging, COVID-19, Viral Pneumonia.

Introduction

Respiratory Viral Infection caused by viruses/bacteria is a widespread disease among humans worldwide. Emerging viruses, such as the novel coronavirus, have caused cases of pneumonia [1]. Pneumonia is a particularly serious and contagious disease caused by microorganism, which affects one or both lungs and shares overlapping clinical and radiological features with COVID-19 [2]. Novel coronavirus also known as COVID-19 is a family of viruses that causes infections and sicknesses from the range of common cold to serious diseases like acute respiratory syndrome etc. [3]. COVID-19 was first discovered in Wuhan city of China. COVID-19 further spreads to other cities, affecting countries all over the world. This has an impact on a high number of people all over the world [4]. Globally, as of June 14, 2025, there have been more than 777 million confirmed COVID-19 cases and more than 7.0 million deaths [5]. In the initial stage of COVID-19, the virus stays in the nose and throat for a while. Later it moves to the lungs and causes a potentially deadly respiratory syndrome [4]. As a result, pus arises in the inhalation way and the growing number of surfactants in the alveoli by the viral attack causes patients to have a cough and a high temperature [6]. On early base detection, the WHO approved the Reverse RT-PCR method [3]. It is more difficult to differentiate between two viral diseases COVID-19 and Viral Pneumonia. This difficulty is an inspiration for the deep learning approaches to diagnose the problem. If a doctor performs the treatment of COVID-19 and Viral Pneumonia patients through Computed Tomography (CT) scan images, they are likely to examine shadows or spotted areas of CT scan known as ”ground glass opacity”, which has a great role in early identification and diagnosis of these viral diseases [6]. However, differentiation in the occurrences of these viral infections is very challenging. To overcome this problem, the machine learning-based technique has been introduced.

Viral pneumonia poses a significant threat to both young children and the elderly, resulting in high mortality rates. According to the Centers for Disease Control and Prevention (CDC), in the United States alone, over one million adults with pneumonia require hospitalization annually, resulting in approximately 50,000 deaths. The World Health Organization (WHO) recognizes chest X-rays as the most effective diagnostic tool for pneumonia [5]. This respiratory infection primarily affects the lungs and can originate from bacterial, viral, or fungal sources. Accurately identifying pneumonia can prove challenging, even for experienced radiologists, due to its resemblance to other lung conditions.

The RT-PCR test has gained much popularity to diagnose malignant patients of COVID-19. In the process, the sample is collected from the nose and throat to detect the viral COVID-19 through RNA. However, the effectiveness of these tests highly depends on the ideal conditions. For example, the researchers at the Foundation for Innovative New Diagnostics achieved 100% accuracy and gained at least 96% specificity on negative cases of COVID-19 patients. The sensitivity is clinically based

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on RT-PCR access from the ranges of 66% to 80% under aberrant and irregular conditions of testing in the real world, proving that testing results of RT-PCR do not work well in the ideal conditions [7]. Chest radiography is an alternative method that has been used for COVID-19 and Viral Pneumonia screening. This involves taking chest X-rays or CT images and analyzing them by radiologists to identify visual markers that may indicate COVID-19 infection. Even if chest X-ray cannot replace RT-PCR testing completely, the presence of pneumonia is a significant sign that a patient is at a higher risk and may require hospitalization. In these cases, chest X-rays can be used to prioritize patient treatment and manage the demands on the healthcare system during the pandemic situation [8].

However, due to the abundant use of radiological images in advanced healthcare organizations, applying a deep learning technique to this problem helps in finding infected patients' cases faster. The proficient deep learning model rapidly identifies irregularities in chest X-ray images, facilitating the detection of cases affected by COVID-19 and Viral Pneumonia. Chest X-rays serve as a customary component in the diagnostic procedure for individuals experiencing respiratory symptoms and can effectively complement conventional RT-PCR testing in establishing an accurate diagnosis [9]. These RT-PCR tests take a long time and cost a lot of money, whereas CNN can help find positive patients automatically. This can improve efficiency to save both time and money, saving lives in the long run.

Furthermore, because none of the current tests are 100% accurate, this can add an extra degree of validation.

A CNN is one of the sub-types of a neural network that consists of two important layers: convolutional layers and pooling layers. The concept of convolutional neural networks originated from recognition, a visual context study conducted by K. Fukushima in 1980 [10]. In 1998, Yann Lecun, Leon Bottou, and Yoshua Bengio made a significant breakthrough in the advancement of CNN by initiating an influential architecture known as LeNet-5 [11].

CNN has been doing exceptionally well in the medical field of imaging. It has been widely utilized in recent years to detect various diseases or anomalies [12]. The occurrence of specialist radiologists are necessary to interpret the pictures if chest X-rays were utilized to screen for a diagnosis. Rather than radiologists, deep learning gives a quick and automatic solution and effective reports in terms of accuracy that may surpass human skills. CNN provides a better solution for patients in the identification of COVID-19 or pneumonia. Different phases of the CNN are used for the classification of the chest X-ray dataset. CNN classifies the image in several stages, resulting in the most accurate classification possible. As a result, algorithms based on CNN are preferred for diagnosing the severe sickness of COVID-19 using the Kaggle dataset [9] [13]. To enhance researchers' comprehension of COVID-19, a comprehensive open-source database was meticulously curated through collaboration with medical experts. To construct these datasets, a wide range of X-ray images was extracted from various publicly available sources, such as publications, along with data indirectly obtained from hospitals and physicians [14].

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Literature Review

In this article, several researchers have developed different models using deep learning techniques to detect COVID-19 from chest X-ray images. They used several datasets containing X-ray images to train their models.

The researchers Jain, et al. [3] used a model called a CNN to classify COVID-19 patients with high accuracy. Another researcher used a similar CNN model and trained it on four different datasets to achieve better accuracy. They also used segmentation masks to focus on relevant areas of the X-ray images [4]. Another model focused on using a smaller number of trainable parameters to diagnose COVID-19. They collected chest X-ray images from 14 institutions and achieved high-performance accuracy [8].

Ahmed, et al. [9] developed a model designed for multi-class classification, aiming to detect COVID-19, Viral Pneumonia, and normal cases. They achieved an average accuracy of 90.64% using a 5-fold cross-validation technique.

Haque and Abdelgawad [12] study utilized three different CNN models to detect COVID-19 patients. They trained and validated their models on two datasets containing images of COVID-19 and normal patients, and achieved exceptional accuracy rates.

One of the deep convolutional models was developed to distinguish between COVID-19, non-detection, and other lung diseases like pneumonia. These models achieved high accuracies of 91.23% for multi-class Fields [15].

Shalini, et al. [16] developed CNNs that were employed to extract chest X-ray characteristics for predictive purposes. When evaluating the model's performance in testing, it considered a broad range of data.

Hafeez, et al. [17] designed a model specifically for real-time detection and diagnosis of COVID-19 using chest X-ray images. These models showed impressive accuracies of 84% to 89% for binary and tertiary classes.

Hariri and Avs¸ar [18] study presents a lightweight differential diagnosis model based on CNNs.

Guefrechi, et al. [19] created a sophisticated deep-learning algorithm designed exclusively for COVID-19 detection utilizing chest X-rays. The experimental findings showcased encouraging outcomes of the proposed models, attaining remarkable accuracy.

Sahin [20] introduced an innovative CNN model for the automated detection of COVID-19 cases through X-ray images. The model aimed to provide a reliable diagnostic tool capable of classifying cases as either COVID-19 or normal. To assess the effectiveness of this approach, a dataset containing 13,824 X-ray images was utilized, and a comparison was conducted with existing COVID-19 detection techniques, focusing on accuracy.

Wang, et al. [21] study produced COVID-Net, which was inspired by the work of the open-source research community. The largest number of 13,975 cases was generated from 13,870 COVID-19 cases. The COVIDx contains a high number of COVID-19 cases and is the open-access dataset.

Ozturk, et al. [22] developed a CNN Darknet-19 that used a small dataset to gain a high performance accuracy of 87.02% for multi-class.

Apostolopoulos and Mpesiana [23] introduced a novel CNN-based technique for

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identifying COVID-19 and Viral Pneumonia through X-ray images. The model is designed for the binary class.

Hemdan, et al. [24] introduced the COVID-19-Net framework and used a dataset of 50 cases of COVID-19, viral pneumonitis, and normal circumstances for their analysis. The results demonstrated an impressive binary classification accuracy effectively distinguishing COVID-19 from normal conditions.

Alazab, et al. [25] proposed a deep CNN system, revealing the significant impact of the virus in coastal areas compared to non-coastal regions.

Rajpurkar, et al. [26], created an algorithm for pneumonia detection using CNN. The algorithm was trained on a set of 100,000 chest X-rays taken from an anterior view, which were provided in the data set. The algorithm was tested using the F1 score metric and the results show that the algorithm achieves an average performance of up to 0.387. On the other hand, the average result of four radiologists was 0.435. The algorithm, however, was limited, in that patient medical history was not considered by the algorithm and not gathered from the radiologists.

X-rays were studied as a standard approach to identify COVID-19 and Viral Pneumonia in a study by Radha [27], The study suggested that use a CNN model to train using a real world dataset of 2,905 lung X ray images downloaded from the Kaggle website. Furthermore, the outcomes achieved by the model in recognising different pneumonia subtypes were promising, with 80% accuracy in recognising Bacterial pneumonia and 91.46% accuracy in recognising Viral pneumonia.

Shadin, et al. [28] suggested two models based on deep learning algorithms using chest X-ray images to identify COVID-19. The researchers used the transfer learning technique to train CNN models using a dataset of 1553 chest X-ray images, yielding an accuracy of 84.92% on the validation set and 79.74% on the training set. Moreover, they studied the InceptionV3 architecture that achieved 85.41% accuracy for training and 84.94% accuracy for validation.

Alotaibi and Alotaibi [29] discussed the dire need for accurate diagnosis of COVID-19 using deep learning techniques. The distinctive method they use is based on the state-of-the-art EfficientNet architecture, pre-trained on the dataset of ImageNet images. This method gave an average accuracy of 89.60% for three-class classification.

By leveraging a diverse dataset encompassing COVID-19, Viral Pneumonia, and normal chest X-ray images, our approach demonstrated high accuracy in distinguishing disease instances. Furthermore, the incorporation of saliency maps enhanced the interpretability of our diagnostic process.

Method

This study utilizes a Convolutional Neural Network (CNN) to detect COVID-19 and viral pneumonia by analyzing chest X-ray images. The model is implemented on the Google Colab platform, utilizing a Graphical Processing Unit (GPU) as the core hardware. To improve algorithm efficiency, the CNN is used for efficient feature extraction, which reduces training duration, mitigates overfitting, and increases accuracy. The model is implemented in four main phases, which are shown in Figure 1.

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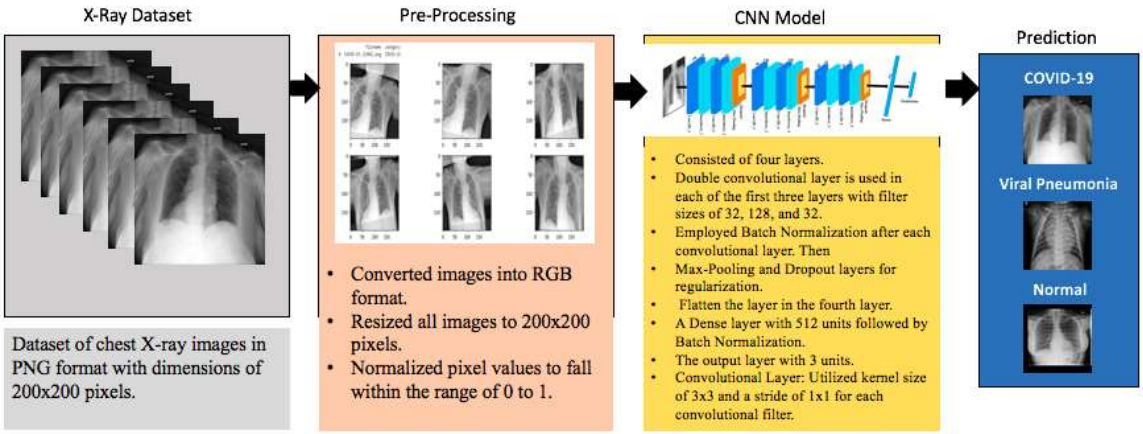


Figure 1. Model flow diagram.

In the first phase, the X-ray dataset COVID-19 Radiograph database was collected from the Kaggle website [9] [13]. which was created with the help of medical doctors to establish an open-source database to assist researchers in understanding COVID-19. The database was collected from various sources, including publications, hospitals, and physicians. In this particular investigation, out of a total of 8500 images, a subset of 3600 images related to COVID-19, 1300 images depicting Viral Pneumonia, and 3600 images representing normal X-rays. Samples of these three classes illustrated in Figure 2, providing a visual representation of the X-ray image used in this study.



Figure 2. Comparison of X-ray image of each cases.

In the pre-processing phase, the dataset is partitioned, with 80% allocated for training and 20% for testing. Each image is resized to 200x200 pixels to ensure uniformity. Within the training set, 20% of the images are reserved for validation, resulting in 5,440 training images, 1,360 validation images, and 1,700 testing images. During pre-processing, the algorithm first checks whether the chest X-ray images are in RGB format. If not, they are converted to RGB to maintain consistency. Each pixel value is then normalized by dividing it by 255, scaling the values to a range of 0 to 1. This normalization is critical for enhancing learning efficiency and enabling faster

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extraction of key image features. The normalization process is mathematically represented as:

$$X = \frac{x}{255}$$

To further improve model robustness and generalization, data augmentation techniques are applied. These include rotation (up to 15°), rescaling (pixel values to 0-1), shearing (maximum 0.1), zooming (maximum 0.2), horizontal flipping, and width/height shifting (maximum 0.1). Such changes produce various variations to the training data, which helps in decreasing over-fitting and the training time. This step ensures standardized input data, facilitating optimal model performance.

The third phase consists of a CNN architecture, illustrated in Figure 3, which is composed of four layers designed for efficient image processing and classification. Each layer has a specific function in feature extraction and regularization. The initial three layers start with a convolutional layer that outputs feature maps with a filter size of 32. Batch normalization is used to stabilize the training process, and then a second convolutional layer is used to reduce the number of output dimensions without changing the size of the filter. The process then goes on to adding another batch normalization followed by max pooling and dropout layers to further enhance generalization and reduce overfitting.

This sequence is repeated for the second and third layers, using filter sizes of 128 and 32, respectively. The stride and kernel size remain consistently maintained at 1 and 3×3, respectively. The data is then flattened into a one-dimensional tensor and passed through a dense layer containing 512 units, followed batch normalization, and dropout for further regularization. The final layer, called Predictions, includes 3 units for classification purposes.

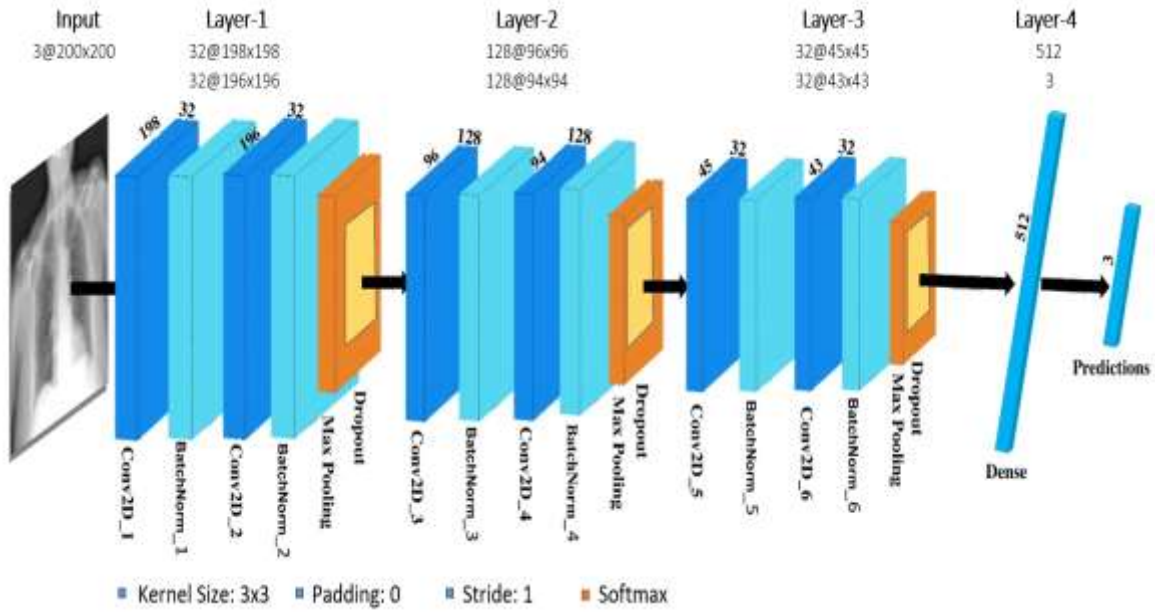


Figure 1. *CNN architecture.*

The model incorporates 7,471,849 parameters and uses categorical cross-entropy as

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the loss function, with Adam as the optimizer with a learning rate of 0.001 and a batch size of 32. To optimize training, a learning rate reduction strategy was implemented, reducing the learning rate by a factor of 0.5 if validation accuracy plateaued for two consecutive epochs.

CNN Model Architecture and Layers

The CNN architecture is designed to extract distinctive features from X-ray images and classify them effectively. Table 1 shows a summary of the model's layers, output shapes, and parameters.

Table 1. Model Summary.

Types of Layers	Output Shape	Parameters
conv2d (Conv2D)	(None, 198, 198, 32)	896
batch normalization	(None, 198, 198, 32)	128
conv2d-1 (Convolution 2D)	(None, 196, 196, 32)	9248
batchnormalization-1	(None, 196, 196, 32)	128
max-pooling2d (Max Pooling 2D)	(None, 98, 98, 32)	0
dropout (Dropout)	(None, 98, 98, 32)	0
conv2d-2 (Convolution 2D)	(None, 96, 96, 128)	36992
batchnormalization-2	(None, 96, 96, 128)	512
conv2d-3 (Convolution 2D)	(None, 94, 94, 128)	147584
batchnormalization-3	(None, 94, 94, 128)	512
maxpooling2d-1 (Max Pooling 2D)	(None, 47, 47, 128)	0
Dropout-1 (Dropout)	(None, 47, 47, 128)	0
conv2d-4 (Convolution 2D)	(None, 45, 45, 32)	36896
batchnormalization-4	(None, 45, 45, 32)	128
conv2d-5 (Convolution 2D)	(None, 43, 43, 32)	9248
batchnormalization-5	(None, 43, 43, 32)	128
maxpooling2d-2 (Max Pooling 2D)	(None, 21, 21, 32)	0
dropout-2 (Dropout)	(None, 21, 21, 32)	0
flatten (Flatten)	(None, 14112)	0
dense (Dense)	(None, 512)	7225856
batchnormalization-6	(None, 512)	2048
dropout-3 (Dropout)	(None, 512)	0
predictions (Dense)	(None, 3)	1539

Total parameters: 7,471,843
Trainable parameters: 7,470,051
Non trainable parameters: 1,792

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Components of the CNN Model

Convolutional Layer

The convolutional layer plays a crucial role in feature extraction by processing input images through convolutional filters, which reduces the output dimensions compared to the input. The convolution operation is mathematically expressed as:

$\sum^{i=n} X * \omega + b$

where X represents the input, ω the filter, and b the bias.

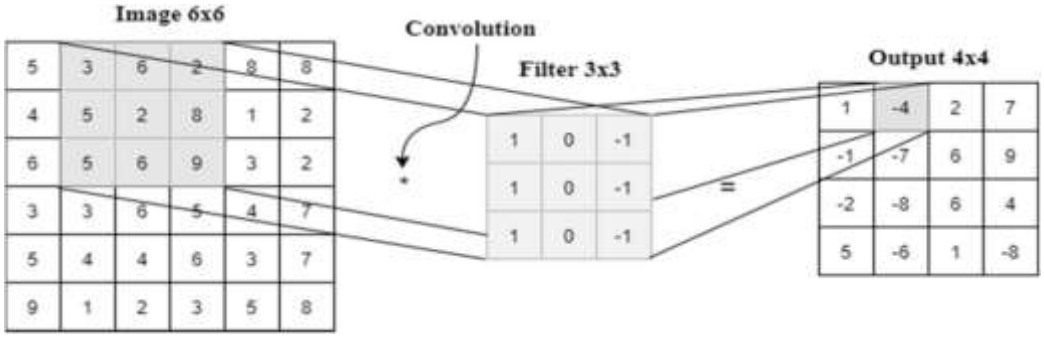


Figure 4. Convolutional Operation.

The dimensions of the output feature map produced by the convolution operation between an input image and a kernel can be determined using Equation 3. This equation incorporates the input size, padding, filter dimensions, and stride values:

$\frac{n+2p-f}{s} + 1$

Here, n corresponds to the input image size, p represents the padding, f denotes the filter size, and s is the stride value. The given equation correctly gives the output size for a convolution operation. For an input size of 200×200, a kernel size of 3×3, a stride of 1, and zero padding, the output dimensions are calculated as 200+2×0−3 +1=198. Thus, the resulting feature map size is 198×198.

The convolution operation is recursively performed by each layer, and the layers further decrease the dimensions of the feature map. As the number of the convolutional layers increases the dimensions of the feature map decreases each time, and after 3 convolutional layers the feature map has a size of 43×43. This reduction in dimension by a series of layers is extremely important for achieving higher level features for successful feature extraction and classification. This operation is carried out over layers, demonstrating the ability of CNNs to work on spatial data.

Batch Normalization

Batch Normalization stabilizes and accelerates neural network training by normalizing activations between layers, mitigating internal covariate shift. It ensures stable input distributions across layers, enhancing convergence and generalization. In this network, Batch Normalization is applied after each convolutional layer without altering the spatial dimensions of the feature maps.

Pooling Layer

The pooling layer reduces input dimensions, decreasing parameters, memory usage, and computational requirements. Max-Pooling is used with a 2x2 kernel and a stride

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Volume 4, Issue 1 (2026)

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Print ISSN 3007-3189
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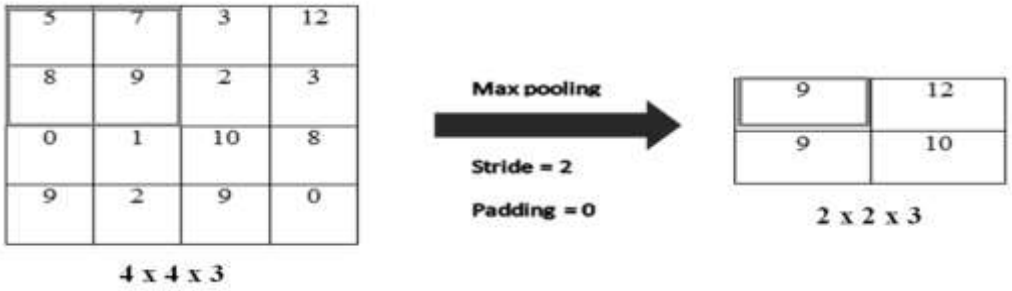


Figure 5. Max pooling operation.

Dropout Layer

Dropout is a regularization technique designed to prevents overfitting in neural networks by randomly deactivating neurons during training. A dropout rate of 0.10 is used for the first three layers, and 0.25 for the final layer.

Dense Layer

The dense layer collects high-level features and makes predictions. Two dense layers are used, the first with 512 neurons and ReLU activation, and the second with 3 neurons for multi-class classification using the Softmax activation function.

The ReLU activation function Used in convolutional layers to introduce non-linearityIt maximizes the linearity range from 0 to infinity, as illustrated in Figure 3.7. The function converts all negative tensor values to zero, ensuring non-linearity while maintaining computational efficiency. Analytically, the ReLU function is represented as:

$$f(\mathrm{x}) = \max(\mathrm{x}, 0)$$

$$f(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

The representation of x in the above equations is used for the input tensor is represent in the figure.

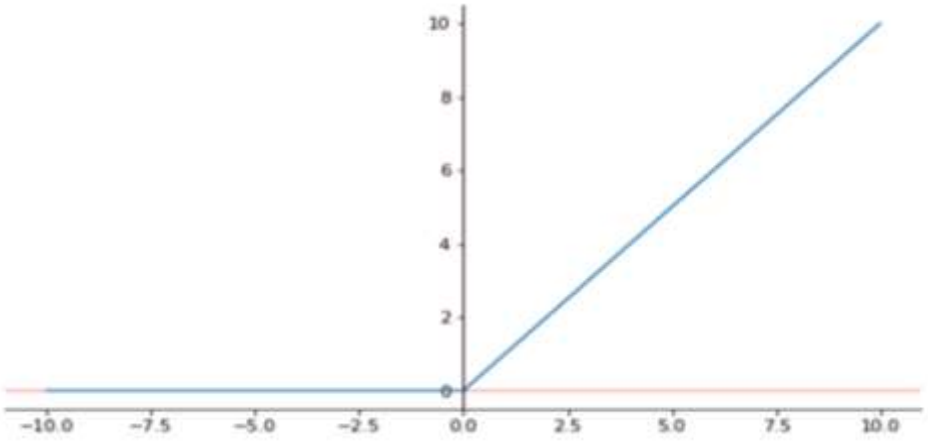


Figure 0.2 ReLU Activation Function.

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The Softmax activation function is a critical decision-making component often used as the output layer in neural networks. It assigns probabilities to input tensors based on their weights, ensuring that the sum of all probabilities equals one, as depicted in Figure 3.8. This function is particularly useful for multi-class classification problems. Mathematically, the Softmax function is expressed as:

$$\frac{e^{x}}{\sum_{j=1}^{n} e^{x j}}$$

Here, xi represents the input tensor, and n denotes the number of inputs. The Softmax function ensures that the output values are normalized and interpretable as probabilities, making it ideal for classification tasks.

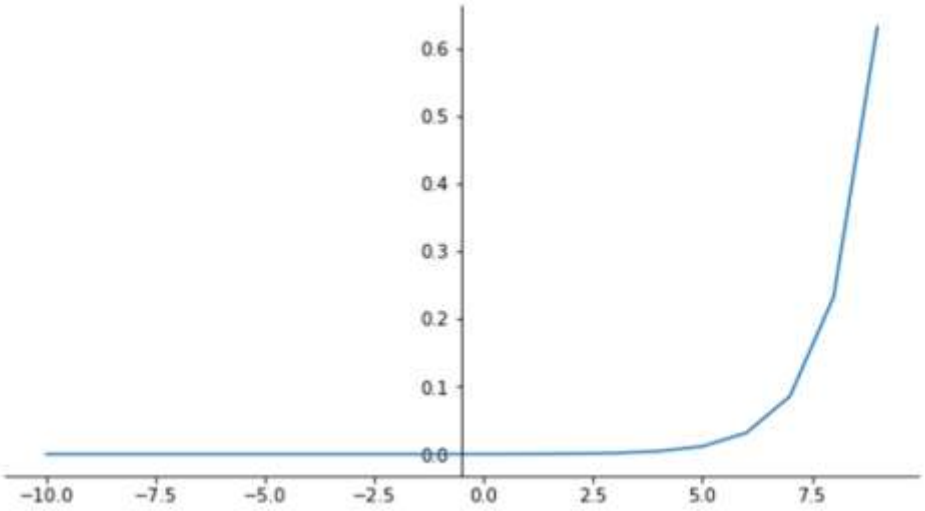


Figure 0.3 Activation function of Softmax.

These activation functions help the model extract features and handle multi-class classification.

Result

The proposed model demonstrated high performance, achieving an average testing accuracy of 91.59%, F1-score of 92.0%, precision of 92.4%, and recall of 91.8%. These results, summarized in Table 2, indicate the model's ability to accurately classify chest X-ray images into COVID-19, Viral Pneumonia, and normal categories.
Model Accuracy: 91.59%
Correct Predictions: 1557 Total Predictions: 1700
Normal Predictions: 620 Accuracy 86.11%
COVID-19 Predictions: 706 Accuracy 98.06%
Viral Pneumonia Predictions: 231 Accuracy 88.85%

Table 2. Result Summary

	Precision	Recall	f1-score	Support
Normal	0.94	0.86	0.9	720
COVID-19	0.87	0.98	0.92	720

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Viral Pneum.	0.99	0.89	0.94	260
Accuracy			0.92	1700
Macro average	0.94	0.91	0.92	1700
Weighted average	0.92	0.92	0.92	1700

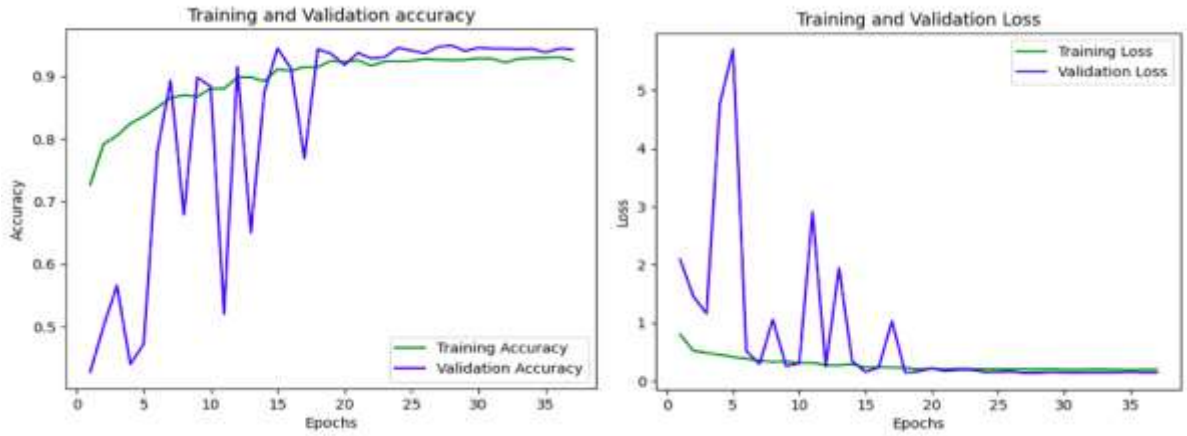


Figure 4. Training, and validation accuracy and loss after 40 epochs.

Discussion

We explore a detailed analysis of model performance using two important tools – confusion matrix and saliency maps. These elements allow us to understand the model behavior and effectiveness in the classification of the COVID-19, Viral Pneumonia and Normal cases captured in the chest X-ray images. The confusion matrix shown in Figure 5 shows a comprehensive evaluation of the CNN model. It gives a tabular comparison between the actual labels of the model predictions for each image.

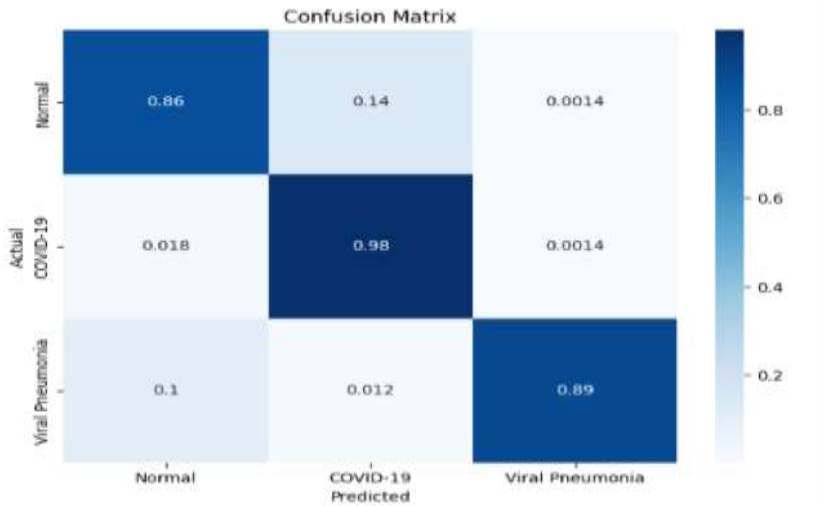


Figure 5. Confusion matrix of the testing set.

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The saliency maps generated from the developed CNN model provided valuable insights, allowing for the identification of influential regions in the input X-ray images illustrated in Figures 6, 7, and 8. These regions represented important characteristics and trends used to make the classification of the model. A comparison of the performance of the model showed that some parts of the saliency maps were highlighted and had a significant contribution to the classification results. These regions helped to better understand the model's arguments and its focus on certain anatomical areas or manifestations of disease.

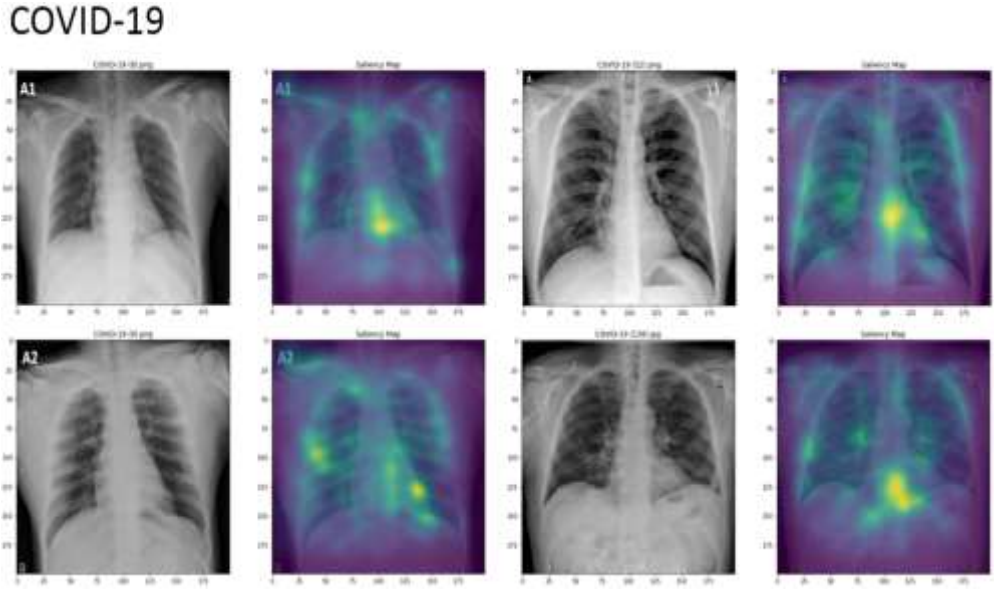


Figure 6. Saliency maps of COVID-19 X-ray images.

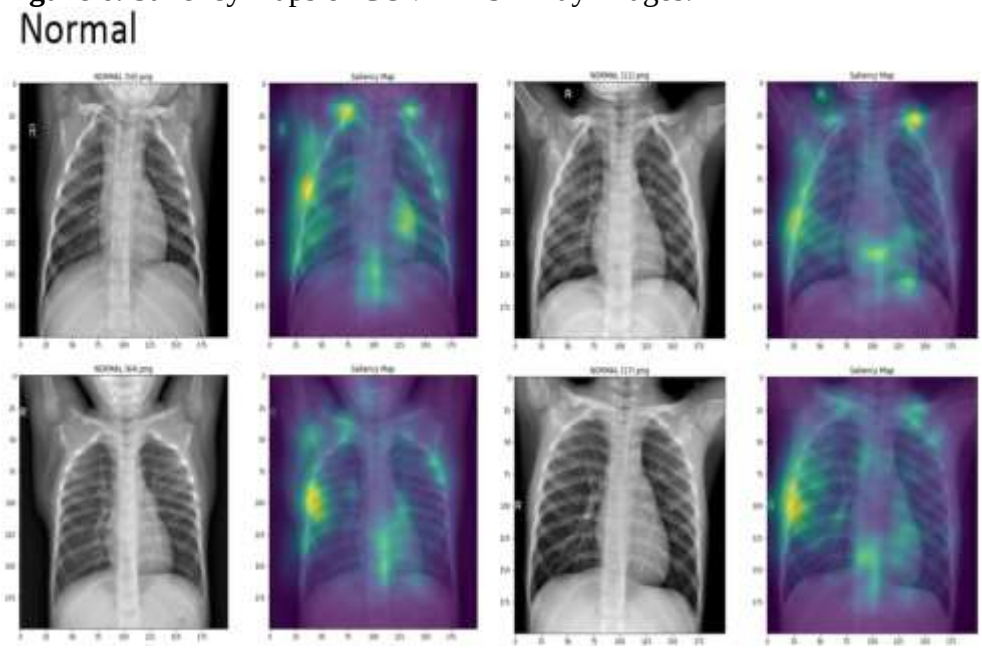


Figure 7. Saliency map of Normal X-ray images.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

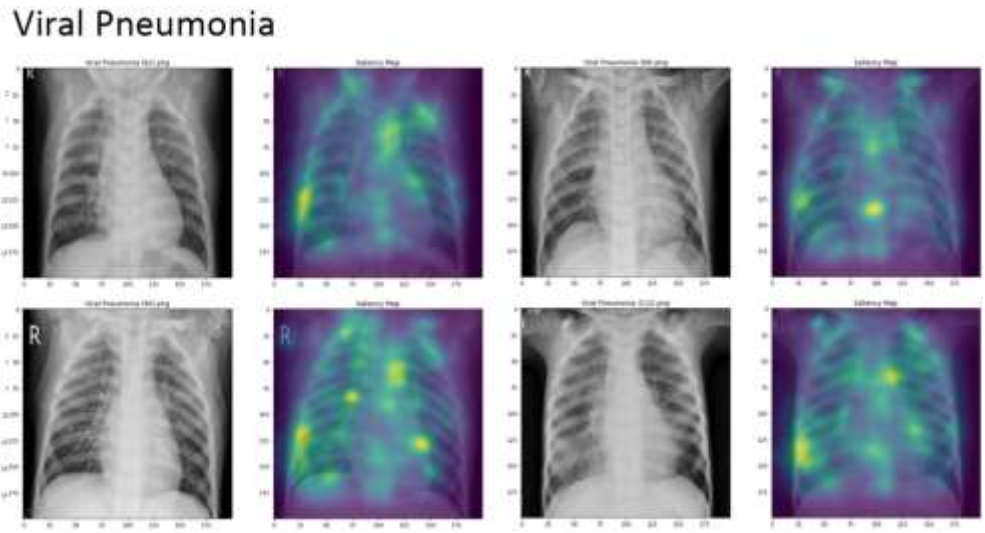


Figure 8. Saliency map of Viral Pneumonia X-ray images.

It was additionally observed that CNN have shown the capability to identify certain patterns in X-ray images that may not be directly linked to the presence of COVID-19. Comparable classification performance can be achieved using X-ray images that exclude a significant portion of lung anatomy. However, it is important to note that until more comprehensive COVID-19 data becomes readily accessible and robust clinical studies are conducted, the utilization of the proposed model as a standalone diagnostic tool may be premature.

Contribution and Impact on Society

Our system represents a significant advancement in the field of disease detection using X-ray imaging analysis. It can differentiate diseases with similar radiographic features, such as COVID-19 and other diseases, which can enhance the accuracy and timeliness of diagnosis. Furthermore, our system can identify COVID-19, and Viral Pneumonia diseases with imaging characteristics which is useful for early detection of outbreaks. This capability makes it a valuable tool for government organizations and clinics that rely on X-ray imagery for disease surveillance.

In a medical environment our system could have a lot of advantages. It is highly accurate, and can serve as a warning system for health care workers and administrators during outbreaks that are just beginning to happen. Our system provides important information and clues, derived from image analysis, to help detect outbreaks and to classify infected cases. It also enhances the patient information system of the organization and would also be useful for prognosis and treatment planning in the future.

Lastly, our deep learning model is a practical solution to the current worldwide medical challenge. Our model is an alternative to the traditional RT-PCR method of testing, which can give a false negative, in just a few minutes and with a more accurate result, as we learn of a growing number of cases of COVID-19 worldwide,

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

and the healthcare resources are becoming stretched thin. By quickly identifying and isolating infected persons, our system could make a substantial impact on infection rates and speed up economic recovery in affected cities.

Conclusion

After assessing the performance of the model, it is evident that CNN can effectively be employed for COVID-19 and Viral Pneumonia screening in chest X-rays. The network reaches an average classification accuracy of 91.59% and an F1 score of 92.0% as a testing solution. This system provides an automated option that can either replace or work alongside manual RT-PCR testing to spot positive patients faster and more effectively. Adopting this deep learning approach helps curb virus transmission, particularly in regions facing severe shortages of test kits. Training the network on larger datasets yields more reliable findings. Running a clinical trial will clarify its actual diagnostic performance before hospitals roll it out worldwide. Article

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