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# Introduction:

The COVID-19 pandemic has presented unprecedented challenges to healthcare systems worldwide. Accurate and timely diagnosis of COVID-19 cases is crucial for effective patient management, resource allocation, and controlling the spread of the virus. While laboratory tests such as polymerase chain reaction (PCR) have been the primary diagnostic method, they often require time-consuming processes and may yield false negatives in certain cases [1]. Complementary diagnostic techniques, such as radiological imaging, can provide valuable insights for identifying and classifying COVID-19 cases.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image analysis and classification tasks in recent years. These algorithms can potentially revolutionize radiology by assisting in the automated interpretation of medical images, including chest X-rays. By leveraging CNNs, researchers and healthcare practitioners aim to develop robust and accurate models for the classification of COVID-19 cases based on X-ray images.

The use of X-ray imaging in COVID-19 diagnosis is particularly advantageous due to its widespread availability, cost-effectiveness, and rapid image acquisition process. Several studies have explored the utility of CNN-based models in analyzing X-ray images to differentiate COVID-19 pneumonia from other lung abnormalities or healthy lung images. These models have shown promising results, demonstrating the potential to aid radiologists in efficiently and accurately identifying COVID-19 cases [2] [3].

This study explores the application of CNNs in the classification of COVID-19 in X-ray images. The aim is to provide an overview of the existing literature, methodologies, challenges, and advancements in this area. By highlighting the potential of CNN-based models, this study significantly contributes to the ongoing efforts to improve COVID-19 diagnosis and enhance patient care.

# Problem Statement

Traditional techniques such as rule-based systems and traditional statistical methods face limitations in COVID-19 classification. Rule-based systems lack adaptability and struggle to capture the complex and evolving patterns of COVID-19 manifestations. They rely on manually defined rules that may not generalize well to new variations. Traditional statistical methods assume independence between variables and have a limited capacity to model non-linear relationships, which may hinder their effectiveness in capturing the intricate patterns in X-ray images. Additionally, ensemble methods, which combine multiple models, require diverse base models that can adequately represent the complexities of COVID-19 manifestations. Constructing diverse models can be challenging, especially when other techniques fail to capture the complexity of the images. Handcrafted feature extraction techniques, dependent on expert knowledge, may overlook important patterns or introduce biases, while dimensionality reduction techniques can result in the loss of spatial information, degrading the classification performance.

In contrast, CNNs offer significant benefits in COVID-19 classification. They automatically learn complex features from the X-ray images, capturing the spatial dependencies and non-linear relationships that traditional techniques struggle to model. CNNs can adapt to changing patterns and generalize well to diverse imaging conditions, allowing for effective classification of COVID-19 cases [4]. Their ability to learn diverse representations without relying on external models makes them well-suited for handling the complexity and variations in COVID-19 manifestations. By leveraging the power of deep learning, CNNs provide a robust and adaptable approach to COVID-19 classification in X-ray images, overcoming the limitations faced by other techniques.

# Literature Review

X-radiation (X-ray) is a widely used method for diagnosing COVID-19, providing detailed chest images that can reveal characteristic features like ground-glass opacities and consolidation. However, interpreting X-ray results can be difficult, especially in cases with mild symptoms or overlapping chest diseases.

To overcome these challenges, researchers have explored machine learning approaches, such as convolutional neural networks (CNNs), to develop automated algorithms for classifying X-ray images as COVID-19 positive or negative. CNNs have demonstrated significant potential in various computer vision applications, including the analysis of medical images.

[Sohaib Asif](https://ieeexplore.ieee.org/author/37088692679); [Yi Wenhui](https://ieeexplore.ieee.org/author/37088691939); [Hou Jin](https://ieeexplore.ieee.org/author/37088692324); [Si Jinhai](https://ieeexplore.ieee.org/author/37088692103) demonstrated a novel method utilizing DCNN and Inception V3 for automated COVID-19 screening on chest X-ray images. The Inception V3 pre-trained model is utilized and trained on COVID-19, normal, and viral pneumonia image, achieving a classification accuracy of more than 98% [5].

[D. Haritha](https://ieeexplore.ieee.org/author/37086276897); [N. Swaroop](https://ieeexplore.ieee.org/author/37088573272); [M. Mounik](https://ieeexplore.ieee.org/author/37088572058) paper presents a transfer learning approach utilizing Googlenet (InceptionV1) for predicting COVID-19 from chest X-ray images. The results demonstrate high training accuracy (99%) and testing accuracy (98.5%), highlighting the effectiveness of transfer learning models in disease prediction [6].

Arivoli, Devdatt Golwala, and Rayirth Reddy proposed a deep learning approach using a Convolutional Neural Network (CNN) created with Keras, integrated with a user-friendly front-end interface named CoviExpert. The model is trained on 1584 Chest X-ray images of both COVID-19-positive and negative patients, with 177 images used for testing. The proposed approach achieves a classification accuracy of 99% [7].

Aras M. Ismael , Abdulkadir Şengür compared deep CNN approaches for COVID-19 detection using chest X-ray images. Deep features with SVM outperformed local descriptors, and fine-tuning and end-to-end training was more time-consuming. The Cubic kernel and ResNet50 model yielded better results, while deep CNN models outperformed shallow networks [8].

Guangyu Jia, Hak-Keung Lam, Yujia Xu put forward a dynamic CNN modification method for classifying COVID-19 CXR and CT image datasets. The proposed method incorporates pointwise convolution blocks to establish connections between different layers, enabling dynamic combinations. Six deep learning algorithms and two COVID-19-specific models are compared, and the modified CNN architecture demonstrates satisfactory classification performance, showing potential for clinical computer-aided diagnosis [9].

The aim of this research is to follow the above-mentioned methodologies to develop and evaluate an image classification model based on Convolutional Neural Networks (CNNs) for COVID-19 classification in X-rays. The use of image classification techniques and CNN models for COVID-19 classification from X-rays falls under the larger field of medical image analysis. This field involves the development of deep learning algorithms and techniques for CNN for the analysis and interpretation of medical images, including X-rays, MRI scans, and CT scans.

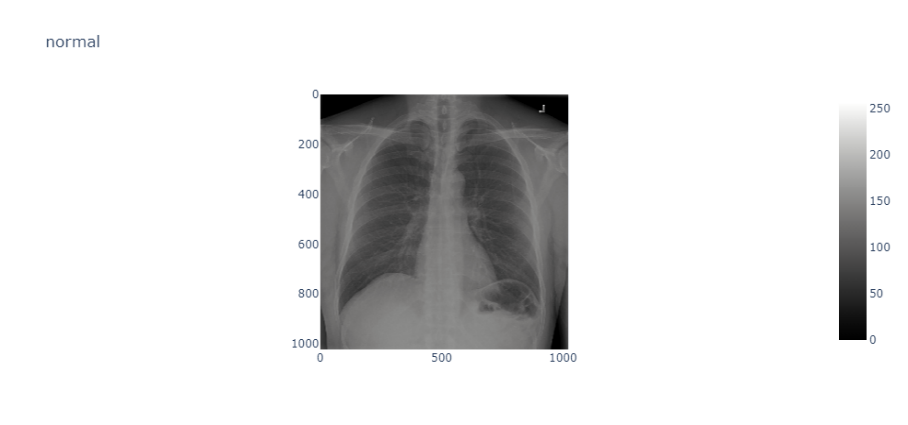
# Proposed Methodology:

To develop this image classification model for COVID-19 prediction in X-rays, we have selected the deep learning approach based on Convolutional Neural Networks (CNN). CNNs have been shown to be highly effective for image classification tasks, making them a natural choice for analyzing medical images.

The dataset used in the study is obtained from famous data set repository Kaggle and it consists of 5,863 chest X-ray images of pediatric patients from Guangzhou Women and Children's Medical Center, categorized into Pneumonia and Normal classes [10]. Prior to training the AI system, all images underwent quality control, with low-quality or unreadable scans being excluded. The diagnoses were then independently graded by two expert physicians, and a third expert reviewed the evaluation set to mitigate grading errors. This rigorous process ensures the reliability and accuracy of the AI system's training and evaluation.



Infected



Normal

Fig.1: X-ray images of Normal and Infected Lungs

The normal chest X-ray shows clear lungs without any abnormal opacification. Bacterial pneumonia is characterized by a focal lobar consolidation, as seen in the right upper lobe. On the other hand, viral pneumonia presents with a diffuse 'interstitial' pattern affecting both lungs.

The system model used for classification is shown in block diagram:

Fig. 2: System Model

Training Loop

(Loss computation)

Classification Model

(ResNet-18)

Results

(Confusion Matrix, Accuracy Graph)

Data Loading

Data Pre-processing

(Resizing, normalization, data augmentation)

Updated Parameters

(Stochastic gradient descent)

Convolutional Neural Networks (CNNs) are powerful deep learning models specifically designed for analyzing visual data, such as images. They have revolutionized the field of computer vision and have been widely used in various applications, including image classification, object detection, and image segmentation. CNNs leverage the concept of convolution, which allows them to capture local patterns and features in an image. By applying multiple convolutional layers with learnable filters, the model can automatically extract hierarchical representations of the input data, enabling it to learn complex patterns and relationships.

CNNs have shown great potential for COVID-19 classification in X-ray images due to their ability to capture intricate details and subtle abnormalities. The multi-layered architecture of CNNs enables them to learn high-level representations of the X-ray images, allowing for accurate differentiation between normal and infected cases.

In this document, we will explore the architecture of a CNN in detail, explaining each component and its role in processing and analyzing images [11].

1. **Input Layer**

The input layer is the first layer of the CNN architecture and serves as the entry point for the image data. It takes in the raw pixel values of the image as input. Mathematically, the input layer can be represented as:

***Input: X***

Where X represents the input image data. The input layer is responsible for processing and preparing the raw image data for further analysis and feature extraction by subsequent layers.

In the case of CNNs, the input layer typically performs some preprocessing steps to standardize the input data and make it suitable for the network's operations. This may involve resizing the input image to a fixed size, normalizing the pixel values, and applying any necessary data augmentation techniques such as random rotations, translations, or flips. These preprocessing steps help in improving the model's robustness and generalization to different variations of the input data.

1. **Convolutional Layer**

The convolutional layer is the core building block of a CNN. It consists of a set of learnable filters or kernels that slide across the input image in a systematic way. Each filter extracts features by performing element-wise multiplications between its weights (W) and a small local region of the input image [12]. These local regions are called receptive fields. Mathematically, the convolutional layer can be represented as:

***Convolution: Z = W \* X***

By stacking multiple convolutional layers, CNNs are able to learn hierarchical representations of the input data. The initial layers capture low-level features such as edges, textures, and gradients, while deeper layers learn more complex and abstract features. This hierarchical feature extraction enables CNNs to effectively model complex relationships in visual data.

For COVID-19 detection using chest X-ray images, the application of CNNs is particularly advantageous. The convolutional layers can learn relevant image features indicative of COVID-19 infection, such as specific patterns in the lung regions or abnormalities associated with the disease. The filters adaptively adjust their weights during the training process to optimize the model's ability to differentiate between COVID+ and COVID- patients based on these learned features.

1. **Activation Layer**

The activation layer applies a non-linear activation function (σ) to the feature map generated by the convolutional layer. The purpose of the activation function is to introduce non-linearity into the model, allowing it to learn complex patterns and make more accurate predictions. Mathematically, the activation layer can be represented as:

***Activation: A = σ(Z)***

One commonly used activation function in CNNs is the Rectified Linear Unit (ReLU), which sets all negative values to zero and keeps positive values unchanged. ReLU has been widely adopted in CNN architectures due to its simplicity and computational efficiency. It helps the model to capture and amplify important features while suppressing irrelevant or noisy information.

1. **Pooling Layer**

The pooling layer is responsible for down sampling the feature maps generated by the convolutional layer. It reduces the spatial dimensions of the feature maps while preserving the most important features. The most commonly used pooling operation is max pooling, which selects the maximum value from a small neighborhood within the feature map. Mathematically, the max pooling operation can be represented as:

***Max Pooling: P = max(A)***

The main advantage of max pooling is its ability to capture the most salient features while discarding irrelevant details. By selecting the maximum value within each pooling region, it ensures that the most activated feature in that region is preserved. This helps in retaining important spatial information and enhancing the network's ability to recognize patterns and objects at different scales.

1. **Fully Connected Layer**

The fully connected layer is a traditional neural network layer that takes the flattened feature map from the previous layer as input. It connects every neuron in this layer to every neuron in the subsequent layer, forming a fully connected network. Mathematically, the fully connected layer can be represented as:

***Fully Connected: F = W \* P***

The fully connected layer introduces additional flexibility to the model by allowing complex relationships and interactions between the features to be captured. It can learn intricate patterns and dependencies that may exist in the data, enabling the network to make more accurate and informed decisions.

In the context of COVID-19 detection using chest X-ray images, the fully connected layer plays a crucial role in combining the extracted features from the convolutional layers and making the final classification decision. By leveraging the information learned from the convolutional layers, the fully connected layer can effectively differentiate between positive COVID-19 cases and negative cases based on the aggregated features.

1. **Output Layer**

The output layer is the final layer of the CNN architecture. It consists of a set of neurons corresponding to the number of classes or categories in the classification problem. Each neuron represents the probability or confidence score of the input belonging to a particular class. The output layer performs a linear transformation of the input followed by an optional activation function to obtain the final output. The output layer can be represented as:

***O = W \* Z + b***

Where:

**O** represents the output of the output layer, which is a vector of class scores.

**W** denotes the weight matrix connecting the previous layer to the output layer.

**Z** represents the input to the output layer, typically the output of the fully connected layer.

**b** denotes the bias vector added to the weighted sum of the inputs.

In the proposed algorithm the *torch.max()* function is used to obtain the predicted class labels. It returns the maximum value and its index along the specified dimension, which corresponds to the predicted class labels [13].

1. **Training and Optimization**

CNNs are trained using a process called backpropagation, which involves iteratively adjusting the weights of the filters and the fully connected layer based on the computed gradients of the loss function. The loss function measures the discrepancy between the predicted output and the true output labels. Mathematically, the loss function can be represented as:

***Loss: L = Σ(y \* log(O) + (1 - y) \* log(1 - O))***

Where y is the true label and O is the predicted output.

In this method to calculate each element of the gradient vector, automatic differentiation provided by deep learning frameworks like PyTorch or TensorFlow is used. Automatic differentiation allows to compute the gradients efficiently without manually deriving and implementing the equations.

The model parameters are updated using the stochastic gradient descent (SGD) algorithm, which involves computing gradients with respect to the loss and updating the weights and biases accordingly. The weight update equation can be represented as:

***W\_new = W\_old - learning\_rate \* gradient***

Where W\_new is the updated weight, W\_old is the previous weight, and the gradient represents the derivative of the loss with respect to the weight.

The process of convolution, activation, and pooling is repeated multiple times in a CNN, forming a deep network architecture. Deeper networks have been shown to learn more abstract and high-level representations, leading to improved performance in complex tasks. However, deeper networks also require more computational resources and may be prone to overfitting if not properly regularized.

1. **Model Evaluation and Testing**

Once the CNN is trained, it is evaluated on a separate test set to assess its performance. Metrics such as accuracy, precision, recall, and F1 score are used to evaluate the model's classification performance. The trained CNN can then be deployed for real-world applications, where it takes new unseen images as input and provides predictions or classifications based on the learned features. The accuracy represents the proportion of correctly classified samples and can be calculated as:

***Accuracy = (Number of correctly classified samples) / (Total number of samples)***

The trained CNN can then be deployed for real-world applications, where it takes new unseen images as input and provides predictions or classifications based on the learned features. The F1 score is a metric used to evaluate the performance of a classification model, particularly in binary classification tasks. It combines the concepts of precision and recall into a single measure that provides a balanced assessment of the model's accuracy.

***F1 Score = 2 \* (Precision \* Recall) / (Precision + Recall)***

Precision represents the accuracy of positive predictions, while recall measures the model's ability to correctly identify positive instances. By taking into account both precision and recall, the F1 score provides a comprehensive evaluation of the model's performance. The F1 score is particularly useful in scenarios where there is an imbalance between the number of positive and negative instances in the dataset. The F1 score considers both false positives and false negatives, making it a more reliable measure of the model's performance in imbalanced datasets.

The confusion matrix summarizes the performance of a classification model. It shows the number of true positives, true negatives, false positives, and false negatives for each class.

# Experimental Results:

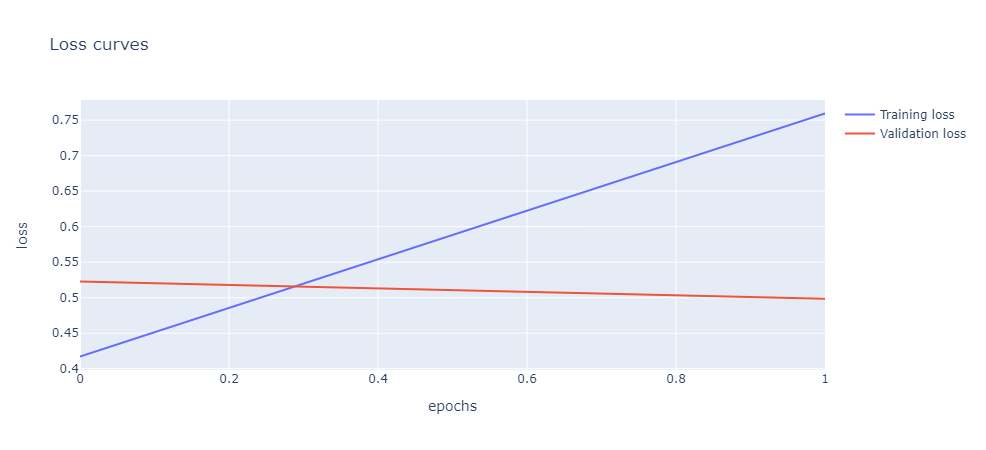
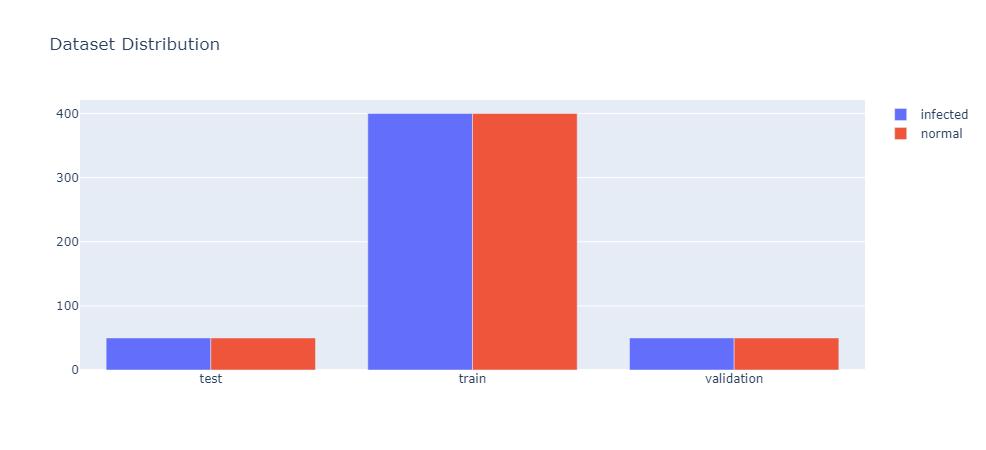
The results of the study show that the CNN model developed using the ResNet-18 architecture was able to achieve an accuracy of 86% on the test set. The test set consisted of 50 normal and 50 infected X-ray images. The confusion matrix for normal X-rays showed that the model correctly classified 46 out of 50 normal images, which is a relatively high rate of accuracy. Similarly, the confusion matrix for infected X-rays showed that the model correctly classified 46 out of 50 infected images. This suggests that the model has a good ability to distinguish between normal and infected X-rays, and has potential for use in diagnosing COVID-19 in patients. However, it is important to note that the study was limited to a specific dataset and further validation is needed on larger and more diverse datasets to determine the generalizability of the model.

Fig. 4: Graph for the Loss Function Gradient

Fig. 3: Histogram of Training, Testing and Validation Data

# Conclusion:

Fig.6: Confusion Matrix of Validation of Predicted Values

Fig. 5: Validation Accuracy Graph

The results of the study demonstrate promising performance of the CNN model in classifying COVID-19 in X-ray images. The model achieved an accuracy of 86% on the test set, indicating its ability to accurately distinguish between normal and infected X-rays. The high accuracy rates in the confusion matrices for both normal and infected X-rays further validate the model's effectiveness in correctly classifying images. These findings suggest that the utilization of CNNs in COVID-19 classification of X-ray images offers a reliable and efficient approach for accurate diagnosis. The robust performance and high accuracy rates achieved by the CNN model highlight its potential as a valuable tool in the early detection and screening of COVID-19, aiding in effective disease management and control. The accurate identification of COVID-19 cases through the CNN model can facilitate timely interventions, such as isolation and treatment, potentially preventing the spread of the virus. Moreover, the model's ability to handle large volumes of X-ray images efficiently makes it suitable for screening purposes in high-throughput healthcare settings.

Future work to improve the limitations of this CNN model for COVID-19 classification in X-rays includes expanding the dataset to encompass a larger and more diverse range of images. Exploring different pre-trained models and architectures, along with applying data augmentation techniques and preprocessing methods, can enhance the model's performance.

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