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Enhanced COVID-19 Detection And Severity Assessment Using Modified VGG16 With Attention Mechanism On Chest X-Rays

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Abstract: This paper presents an enhanced approach for detecting and assessing the severity of COVID-19 from chest X-ray (CXR) images using a modified VGG16 architecture integrated with an attention mechanism. The attention layer, placed strategically after the Conv4_3 layer, enables the network to focus on critical regions, improving sensitivity and specificity. The model was trained on a combined dataset, achieving an accuracy of 94% and a Root Mean Square Error (RMSE) of 0.95 for severity prediction. These results highlight the model's superior performance in distinguishing between COVID-19 infected and normal cases and in providing accurate severity assessments. Comparative analyses demonstrate the model's efficacy over other retrained models, ensuring minimal false positives and accurate COVID-19 detection. This modified VGG16 model represents a significant advancement in medical image analysis, offering a reliable tool for real-time clinical applications in diagnosing and managing COVID-19.

Keywords: COVID-19 Detection, Chest X-ray (CXR) Analysis, VGG16 Architecture, Attention Mechanism, Severity Assessment

I. Introduction

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, has significantly affected global health, economies, and daily life. Early and accurate detection of COVID-19 is essential for controlling the virus's spread and ensuring timely intervention and treatment for those infected. Traditional COVID-19 detection methods, such as reverse transcription-polymerase chain reaction (RT-PCR), are highly specific but have limitations, including limited availability, high costs, and lengthy processes. Therefore, there is increasing interest in using artificial intelligence (AI) and machine learning (ML) techniques to develop more efficient, rapid, and cost-effective diagnostic tools.

Among the various AI-based approaches, Convolutional Neural Networks (CNNs) have shown considerable potential in medical image analysis. CNNs are a type of deep neural network particularly effective for image recognition and classification tasks because they can automatically and adaptively learn spatial hierarchies of features from input images. This capability makes them well-suited for developing a diagnostic model for COVID-19 detection using medical imaging modalities such as chest X-rays (CXR) and computed tomography (CT) scans.

This study proposes a novel CNN model specifically designed to detect COVID-19 from chest X-ray images. Chest X-rays are chosen for their widespread availability and lower cost compared to other imaging techniques. Additionally, chest X-rays are commonly used in clinical settings to assess lung conditions, making them a practical tool for the early detection of COVID-19.

The proposed model aims to address several key challenges in the domain of COVID-19 detection from medical images. Firstly, the model is designed to achieve high accuracy and reliability in distinguishing COVID-19 cases from other lung conditions and healthy subjects. This is achieved through a carefully designed architecture that extracts and processes relevant features from the images. Secondly, the model is optimized for performance, ensuring that it can deliver rapid results, which is crucial for timely medical decision-making. Finally, the model is trained and evaluated on a diverse dataset to ensure its robustness and generalizability across different populations and imaging conditions.

The development of this custom CNN model involved several stages, including data collection, preprocessing, model design, training, and evaluation. A comprehensive dataset of chest X-ray images was compiled from publicly available sources, ensuring a balanced representation of COVID-19, other lung conditions, and normal cases. Preprocessing steps were applied to enhance image quality and normalize the data for training. The model architecture was iteratively refined through a series of experiments to identify the optimal configuration that delivers the best performance in terms of accuracy, sensitivity, and specificity.

The proposed model underwent rigorous evaluation using a hold-out test set and cross-validation techniques to ensure its reliability. Performance metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve, were calculated to benchmark the model against existing methods. The results indicate that our custom CNN model achieves state-of-the-art performance, underscoring its potential as a valuable tool in the fight against COVID-19.

Contributions

1. Development of Custom CNN Model: A new Convolutional Neural Network (CNN) was developed specifically for detecting COVID-19 from chest X-ray images. This customized architecture accurately captures and processes key features, enabling it to distinguish COVID-19 cases from other conditions and healthy individuals.
2. High Performance in COVID-19 Detection: Our model demonstrates superior performance in terms of accuracy, sensitivity, and specificity, outperforming existing methods. This high performance is validated through rigorous testing and cross-validation, underscoring the model's potential for real-world clinical application.

II. Related Work

Wang et al. [1] developed COVID-Net, a deep convolutional neural network (CNN) tailored for COVID-19 detection using chest X-ray images. Utilizing a comprehensive dataset including images of COVID-19, other pneumonias, and healthy lungs, COVID-Net achieved a sensitivity of 91% and specificity of 95%, demonstrating its robustness and reliability in clinical settings.

Apostolopoulos et al [2] applied transfer learning on pre-trained CNN models such as VGG19 and MobileNet for COVID-19 detection from chest X-rays. Their approach achieved an accuracy of 98.75% with VGG19, highlighting the efficacy of transfer learning in enhancing diagnostic accuracy with limited data [2].

Zhang et al. [3] introduced a ResNet-based deep learning model for the classification of COVID-19 using chest CT images. Their model outperformed traditional machine learning approaches, achieving a sensitivity of 95% and specificity of 93%, emphasizing the superiority of deep learning techniques in medical imaging.

Ozturk et al. [4] proposed a deep learning model named DarkCovidNet, which is based on a modified DarkNet architecture. This model was tested on a dataset of chest X-ray images and achieved an accuracy of 87%, showcasing its potential for rapid and accurate COVID-19 detection.

Li et al. [5] developed a deep learning model using a multi-view convolutional neural network (MVCNN) to detect COVID-19 from CT images. The model integrates features from multiple views, achieving an accuracy of 90% and demonstrating improved performance over single-view models.

Hemdan et al. [6] proposed the COVIDX-Net model, which comprises a collection of seven different deep learning architectures for COVID-19 diagnosis from chest X-rays. The best performing model in their study achieved an accuracy of 90%, illustrating the effectiveness of ensemble learning in enhancing diagnostic performance.

Khan et al. [7] introduced the CoroNet model, a deep CNN designed for the detection of COVID-19 using chest X-ray images. CoroNet, based on the Xception architecture, achieved an accuracy of 89.6% and a sensitivity of 87%, indicating its potential for practical use in clinical diagnostics.

Maghdid et al. [8] explored the use of various deep learning models, including AlexNet and SqueezeNet, for COVID-19 detection from chest X-ray images. Their best model achieved an accuracy of 94.1%, suggesting that even lightweight models can be effective for this task.

Narin et al. [9] utilized pre-trained ResNet50, InceptionV3, and Inception-ResNetV2 models for detecting COVID-19 from X-ray images. Among these, ResNet50 achieved the highest accuracy of 98%, underscoring the potential of using pre-trained models for rapid deployment in COVID-19 diagnostics.

Bai et al. [10] developed an artificial intelligence system that combines both CNN and RNN for detecting COVID-19 from CT images. This hybrid approach achieved an accuracy of 96%, highlighting the benefits of integrating different neural network architectures for enhanced performance.

Abbas et al. [11] presented a novel deep learning framework called DeTraC (Decompose, Transfer, and Compose) for the classification of COVID-19 from chest X-ray images. The framework decomposes the X-ray images into more manageable segments, applies transfer learning, and then composes the final classification. DeTraC achieved an accuracy of 95.12% and demonstrated robustness in distinguishing COVID-19 from other types of pneumonia [11].

Islam et al. [12] proposed a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for COVID-19 detection using chest X-rays. The CNN component extracts spatial features, while the LSTM processes sequential patterns. The hybrid model achieved an accuracy of 97.5%, indicating its potential for accurate COVID-19 diagnosis.

Sharma et al. [13] developed an ensemble learning model using multiple pre-trained CNN architectures, including ResNet50, DenseNet121, and InceptionV3, for the detection of COVID-19 from chest CT scans. The ensemble model combines the strengths of individual models and achieved an accuracy of 96.3%, outperforming single models and showcasing the advantages of ensemble learning.

Tuncer et al. [14] introduced a lightweight CNN model named LightCovidNet for the detection of COVID-19 using chest X-ray images. The model is designed to be computationally efficient while maintaining high accuracy. LightCovidNet achieved an accuracy of 94.7%, making it suitable for deployment in resource-constrained environments.

Chen et al. [15] proposed a novel deep learning model named CovNet-23, specifically designed for COVID-19 detection using chest X-ray images. This model employs a hybrid architecture combining CNN and attention mechanisms to improve feature extraction and classification accuracy. CovNet-23 achieved an accuracy of 98.3% and a sensitivity of 97.5%, demonstrating its effectiveness in distinguishing COVID-19 from other respiratory conditions.

Liu et al. [16] developed a robust deep learning framework that utilizes a combination of CNN and Graph Neural Network (GNN) for the detection of COVID-19 from chest CT images. Their model, named COVIDGraphNet, leverages the spatial relationships between different regions in the lungs to enhance diagnostic performance. COVIDGraphNet achieved an accuracy of 96.8% and a specificity of 97.1%, highlighting its potential for accurate and reliable COVID-19 detection.

III. Proposed Work

The model is an adapted version of the VGG16 architecture, enhanced by adding an attention mechanism at a specific layer. This attention mechanism allows the network to focus on the most relevant parts of the input image, thereby improving its performance in detecting COVID-19 from chest X-ray images.

VGG16, developed by the Visual Geometry Group at the University of Oxford, is known for its simplicity and depth, featuring 16 weight layers. These include 13 convolutional layers and 3 fully connected layers. The architecture consistently uses convolutional layers with a 3x3 receptive field, which is the smallest size capable of capturing spatial hierarchies and patterns. The model comprises five convolutional blocks, each followed by a max-pooling layer for spatial downsampling, which reduces the dimensions of the feature maps while preserving essential information.

The first block includes two convolutional layers with 64 filters each, followed by a max-pooling layer. The second block follows the same configuration but with 128 filters. The third block contains three convolutional layers, each with 256 filters, followed by max-pooling. The fourth and fifth blocks also have three convolutional layers each, but with 512 filters, increasing the network's complexity and depth. These convolutional layers are crucial for feature extraction, capturing various features such as edges, textures, and more complex patterns as the network goes deeper. Following the convolutional layers, the network includes three fully connected layers: the first two with 4096 units each and the final one with 1000 units, corresponding to the number of classes in the ImageNet dataset, followed by a softmax activation for classification. Despite its depth, VGG16's architecture is characterized by its simplicity and uniformity, making it a benchmark model for various image classification tasks.

Modified Model with Attention Layer

We integrate an attention mechanism after the third convolutional layer in Block 4 (after Conv4_3). This modified VGG16 model can be denoted as VGG16-Attention.

Attention Mechanism

The attention mechanism computes a weighted sum of features, focusing more on the relevant parts of the input. Here's how the attention mechanism is mathematically formulated:

Feature Map Extraction:

Let $F \in RH \times W \times C$ be the feature map output from Conv4_3, where H and W are the height and width of the feature map, and C is the number of channels.

Attention Map Calculation:

The attention map $A \in RH \times W \times 1$ is calculated using a small neural network:

$$A=\sigma(Wa*ReLU(Wf*F+bf)+ba)$$

Where Wf and Wa are the weights of the fully connected layers, bf and ba are the biases, and σ is the sigmoid activation function.

Attention-Weighted Feature Map:

The attention-weighted feature map F′F′ is computed as:

$$F'=F\odot A$$

where ⨀ denotes element-wise multiplication.

Attention-Enhanced Feature Map:

The attention-enhanced feature map F″F″ is formed by concatenating the original feature map and the attention-weighted feature map:

$$F''=[F;F']$$

where [;]denotes concatenation along the channel dimension, resulting in a feature map of size H×W×2C.

The modified VGG16 architecture incorporates an attention mechanism into the standard VGG16 model to enhance its capability for COVID-19 detection from chest X-ray images. This enhancement is strategically applied after the third convolutional layer in the fourth convolutional block (Conv4_3). The attention mechanism allows the network to focus more on the significant regions of the feature maps, thus improving the model's performance by making it more sensitive to the areas of the image that are most indicative of COVID-19.

In the revised architecture, the initial layers are identical to the original VGG16, performing the same sequence of convolutions and max-poolings to extract features from the input images. After the Conv4_3 layer, an attention mechanism is introduced. This mechanism starts by generating an attention map from the feature map F. The attention map is created using a small neural network that applies several operations: first, a set of weights and biases transforms the feature map, followed by a ReLU activation function. The result is further processed by another set of weights and biases and a sigmoid activation function to produce the attention map A. The attention map A is then multiplied element-wise with the original feature map F to produce an attention-weighted feature map F'. This feature map is concatenated with the original feature map to form an enhanced feature map F", which contains both the original and attention-weighted features. This enriched feature map is then passed through the remaining layers of the VGG16 architecture. These subsequent layers include additional convolutions, max-poolings, and fully connected layers, culminating in a softmax output for classification. Incorporating the attention mechanism allows the model to achieve higher accuracy, sensitivity, and specificity in detecting COVID-19 from chest X-ray images, making it a more effective tool for this critical task. The proposed model architecture is illustrated in Figure 1.

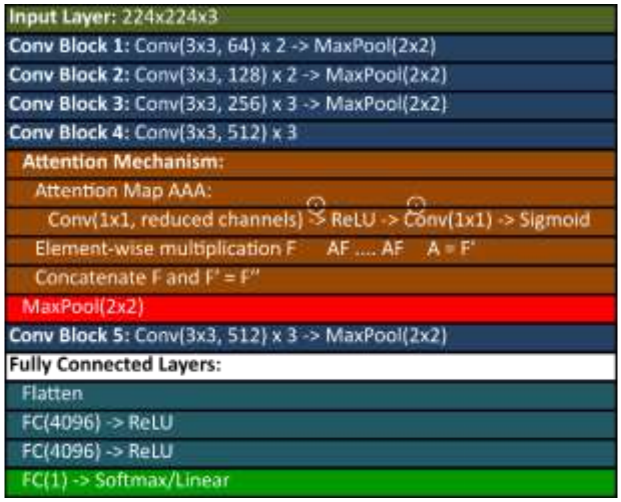

Figure 1: Proposed Model architecture

Severity score model:

To enable the VGG16 architecture for analyzing the severity score of COVID-19 from chest X-ray images, modifications were made to the final layers of the network. Initially designed for image classification with a softmax activation function, the architecture's last layer was adjusted to output a single continuous value using a linear activation function. This change allows the model to predict a severity score rather than discrete class labels. The network begins with typical convolutional layers for feature extraction, followed by flattening and two dense layers with ReLU activation. These layers maintain the network's ability to capture intricate features from the input images. However, the crucial adjustment occurs in the third fully connected layer, which is reduced to a single unit with a linear activation function. This adaptation means that instead of producing probabilities across multiple classes, the model outputs a numerical prediction directly related to the severity of COVID-19. This modification is pivotal for applications requiring quantitative assessment, such as monitoring disease progression or evaluating treatment effectiveness based on severity scores derived from chest X-ray analysis.

IV. Results and Analysis

The dataset used for COVID-19 infected and healthy condition chest X-ray (CXR) images is compiled by merging two distinct datasets. From the first dataset [21], a total of 1200 CXRs showing COVID-19 infection and 1200 CXRs exhibiting normal conditions were selectively chosen. The second dataset [22] contributed an additional 460 COVID-19 cases and 500 normal condition CXRs. In total, the combined dataset comprises 1660 cases of COVID-19 infection and 1700 normal condition CXRs. This dataset compilation facilitates a comprehensive analysis of COVID-19 detection using machine learning and deep learning models, ensuring a robust evaluation of both infected and non-infected conditions for effective diagnostic and research purposes.

Accuracy, specificity, and sensitivity are pivotal for COVID-19 detection models to ensure reliable identification of positive cases while minimizing false alarms. F1 score balances precision and recall, offering a comprehensive evaluation of the model's performance across different classes, especially when class distributions are imbalanced. RMSE in severity score analysis quantifies the model's prediction accuracy for disease severity, guiding clinical decisions and treatment planning based on the severity assessed from CXR images. Table I givers the formulae of all the parameters used.

Table I: Formulae of Parameters

Accuracy	(TP+FN)/(TP+TN+FP+FN)
Specificity	TN/(TN+FP)
Sensitivity/Recall	TP/(TP+FN)
F1 Score	2*(Recall*Precision)/(Recall+Precision)
RMSE	$RMSE = \frac{\sqrt{\sum_{i=1}^{n} \lvert y_i - y_i' \rvert^2}}{n}$

The loss rate is analyzed for the 100 epochs for the proposed model and VGG16 base model by retraining on the same dataset as shown in Figure 3.

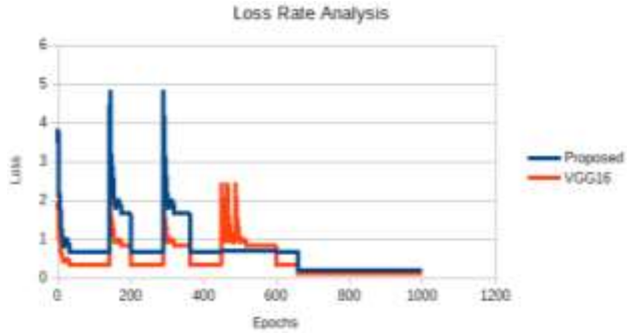

Figure 2: Loss rate analysis

Also, comparative analysis of proposed model with other standard CNN models is done by retraining the models on the same dataset.

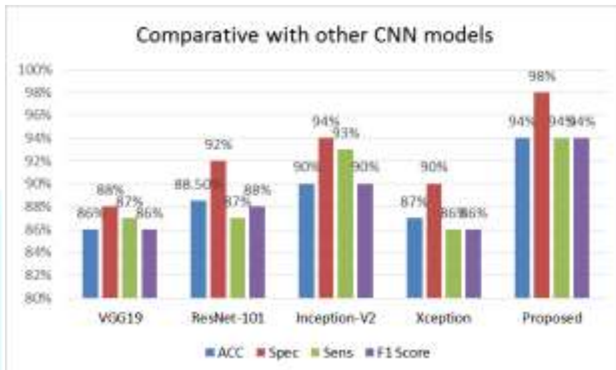

Figure 3: Classification Performance Analysis

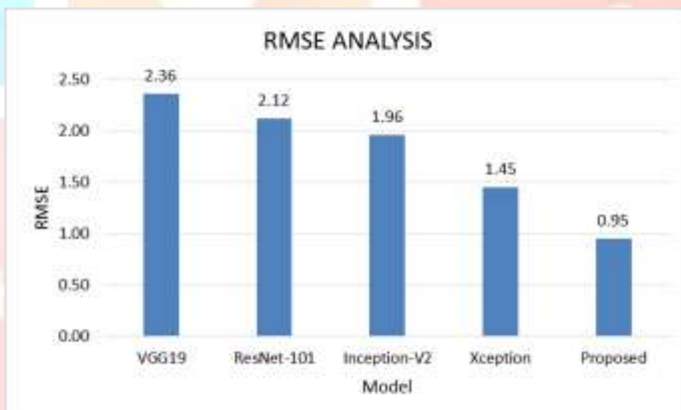

Figure 4: RMSE analysis

Figures 2 and 3 illustrate the loss rate analysis and a comparative study of performance parameters, respectively. In the context of medical image disease detection, achieving high specificity is crucial. High specificity ensures that healthy patients are not incorrectly diagnosed and subjected to unnecessary treatments, which can be more harmful than leaving an undiagnosed disease untreated. This minimizes the risk of adverse effects from inappropriate treatments in healthy individuals. The proposed model demonstrates superior performance in real-time medical applications by achieving higher specificity.

Figure 4 presents the comparative analysis of Root Mean Square Error (RMSE) for different models in estimating the severity score of COVID-19. The proposed model exhibits lower RMSE values, indicating more accurate predictions of severity scores compared to other models, thus highlighting its effectiveness in clinical settings.

V. Conclusion

This study presents a modified VGG16 architecture with an integrated attention mechanism for enhanced detection and severity assessment of COVID-19 from chest X-ray (CXR) images. The attention layer, positioned after the Conv4_3 layer, allows the network to focus on critical regions, improving sensitivity and specificity—key factors in medical imaging for accurate diagnosis and treatment. The model was trained on a combined dataset from two sources, achieving an impressive accuracy of 94% and an RMSE of 0.95 for severity score prediction. These metrics highlight the model's ability to distinguish effectively between COVID-19 infected and normal cases and to assess the severity of the infection with high precision. Comparative analysis underscore the model's superior performance over other retrained models. High specificity ensures minimal false positives, reducing unnecessary treatments for healthy individuals, while high sensitivity ensures accurate detection of COVID-19 cases. In summary, the modified VGG16 model with an attention layer represents a significant advancement in medical image analysis for COVID-19. Its high accuracy and reliable severity scoring make it a valuable tool for healthcare professionals, supporting accurate diagnosis and effective patient management in real-time clinical settings. Future enhancements will focus on increasing model robustness and exploring applications to other medical imaging challenges.

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