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COVID-19 INFECTION SCORE ESTIMATION USING CONVOLUTION NEURAL NETWORK USING CHEST X-RAY IMAGES

Ms.J.C.Patil[1], Mr.Prof.A.V.Shaha[2]

Electronics And Telecommunication Dept, D.K.T.E.Textile & Engineering Institute, Ichalkaranji, India[1]

Electronics And Telecommunication Dept., D.K.T.E.Textile & Engineering Institute, Ichalkaranji, India[2]

Abstract: The COVID-19 pandemic, caused by the SARS-CoV-2 virus, has led to a global health crisis with significant morbidity and mortality. Effective screening methods are crucial for controlling its spread, but existing pathological tests have limited accuracy. Chest radiography imaging, including X-rays and CT scans, offers an adjunctive screening approach, yet interpretation challenges persist due to subtle markers and similarities with other pulmonary diseases. Deep learning architectures, particularly convolutional neural networks (CNNs), present a promising avenue for enhancing diagnostic accuracy. This study explores the modification of the VGG16 model with an attention layer to improve COVID-19 detection from chest X-ray images. The attention layer highlights relevant features, aiding in the identification of infection markers. Additionally, the model is extended to estimate infection severity, enhancing its diagnostic capabilities. Performance evaluation demonstrates promising results, suggesting the potential impact of attention-based modifications in refining existing architectures for improved COVID-19 screening. This research contributes to the evolving landscape of using deep learning models for COVID-19 detection and severity estimation, offering insights for future research and applications.

Keywords: Mean squared error (MSE), mean absolute error (MAE), Acute Respiratory Distress Syndrome (ARDS),convolutional neural networks (CNNs).

I. INTRODUCTION

The COVID-19 pandemic, initiated by the SARS-CoV-2 virus, has reverberated across the globe, profoundly impacting public health with widespread illness and significant mortality. As of May 28, 2020, reported cases had surged beyond five million, with a staggering death toll of 353,373 spanning 216 countries. While many individuals exhibit mild symptoms, others develop severe conditions, such as pneumonia, highlighting the heterogeneous nature of the disease manifestation.

Effective containment of the virus hinges upon robust screening methods. However, conventional pathological tests suffer from reported accuracies ranging between 30% to 60%, presenting substantial limitations. Particularly for patients with severe respiratory conditions like pneumonia and Acute Respiratory Distress Syndrome (ARDS), adjunctive screening via chest radiography imaging, including X-rays or CT scans, becomes indispensable. These imaging modalities aim to pinpoint specific markers associated with SARS-CoV-2 viral disease. Nonetheless, interpreting these images poses considerable challenges due to the subtlety of disease indicators, necessitating high levels of radiological expertise.

In this milieu, the exploration and refinement of deep learning architectures, notably convolutional neural networks (CNNs), emerge as a promising avenue. These models leverage their capacity to extract intricate features from medical imaging data, potentially enhancing the identification of COVID-19 markers. Integration of such models into diagnostic processes holds promise for improving sensitivity and specificity in COVID-19 screening from chest radiography, thereby providing indispensable support to healthcare professionals in decision-making.

The dynamic nature of the battle against COVID-19 underscores ongoing efforts to enhance screening methodologies. Scientific inquiry delves into innovative technologies and methodologies with the overarching goal of bolstering diagnostic capabilities, mitigating false positives and negatives, and ultimately contributing to effective virus management and containment.

This study presents a modification to the VGG16 model, incorporating an attention layer. This addition, integrating max pooling and average pooling within the attention layer, aims to extract more relevant features compared to the conventional VGG16 model. Anticipated benefits include enhanced accuracy in detecting COVID-19 from chest X-ray (CXR) images.

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The attention layer accentuates specific regions of interest within CXR images, enabling focused scrutiny of critical details indicative of COVID-19 infection. Synergistic pooling techniques contribute to a nuanced feature extraction process, capturing subtle patterns associated with the viral disease.

Furthermore, this research extends beyond mere detection, encompassing an additional layer focused on estimating infection severity. By retraining the modified model, comprehensive analyses extending beyond binary classification are envisioned. This aligns with broader objectives of leveraging advanced computational techniques to extract valuable insights from medical imaging data.

Performance evaluation of the modified VGG16 model, encompassing both initial COVID-19 detection and subsequent severity estimation, unveils promising advancements. The integration of attention mechanisms within established models heralds a proactive approach to refining existing architectures for improved diagnostic capabilities. Positive outcomes underscore the potential impact of such modifications in bolstering the accuracy and depth of insights derived from medical imaging data.

II. LITERATURE REVIEW

Recent advancements in medical imaging have spurred a notable surge in the adoption of advanced diagnostic techniques, particularly for the rapid analysis of chest X-rays. This trend is underpinned by several factors, including the lower levels of ionizing radiation exposure and the inherent portability of X-ray imaging equipment. Chest X-rays offer considerable advantages in medical imaging, notably including significantly lower radiation exposure compared to chest CT scans, which is crucial in scenarios prioritizing minimal radiation dose. Additionally, the portability of chest X-ray equipment enables prompt decision-making and facilitates patient management, particularly in emergency situations where quick diagnoses are imperative.

While chest CT scans provide high-resolution three-dimensional images, the pragmatic advantages of chest X-rays make them preferable in various clinical scenarios due to their cost-effectiveness, accessibility, and reduced radiation exposure. Notably, recent studies have showcased the potential of convolutional neural networks (CNNs) in contributing to the rapid and accurate identification of COVID-19 cases through the analysis of chest X-ray images.

Wang et al. leveraged a sophisticated CNN to analyze chest X-ray images, achieving an impressive classification accuracy of 98.9%. Similarly, Hemdanetal. introduced COVIDX-Net, a neural network tailored for automated COVID-19 identification from chest X-ray images, achieving a classification accuracy of 91%. These studies highlight the efficacy of CNNs in discerning distinct patterns indicative of COVID-19 within chest X-ray images.

Narin et al. explored the performance of different CNN architectures for COVID-19 classification, with ResNet-50 emerging as the standout performer, boasting a remarkable accuracy of 98%. Their study underscores the importance of selecting appropriate model architectures tailored to the specific task of COVID-19 classification from medical images.

Incorporating transfer learning techniques, Asif and Wenhui achieved a classification accuracy of 96% using the Inception V3 architecture, highlighting the effectiveness of leveraging pre-existing knowledge for COVID-19 detection. Similarly, Farooq and Hafeez showcased the potential synergy between deep learning and traditional machine learning techniques, achieving accuracies of 90.5% and 81% using SVM and Random Forest algorithms, respectively, for COVID-19 detection from chest X-ray images.

Furthermore, interpretability emerged as a key focus in recent studies, with models like Deep COVID Explainer emphasizing the importance of understanding localized abnormalities within chest X-ray images. This approach facilitates better integration of AI systems with healthcare decision-making processes, enhancing trust and transparency in model predictions.

Overall, these studies demonstrate significant progress in leveraging advanced computational models, particularly CNNs, for the detection and diagnosis of COVID-19 from chest X-ray images.

However, challenges such as dataset variability, generalizability, and interpretability of model decisions remain crucial considerations for the seamless integration of these models into clinical practice. Further research and validation efforts are essential to address these challenges and ensure the reliability and effectiveness of AI-driven approaches in medical imaging.

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III. OBJECTIVES

1. **Objective 1: Enhancing COVID-19 Detection Accuracy:** The primary objective is to enhance the accuracy of COVID-19 detection from chest X-ray images by modifying the VGG16 model with an attention layer. This modification aims to extract more relevant features, thereby improving the sensitivity and specificity of the model in identifying COVID-19 markers.
2. **Objective 2: Estimating Infection Severity:** Another objective is to extend the modified VGG16 model to estimate infection severity. By retraining the model, comprehensive analyses beyond binary classification are envisioned. This objective aligns with the broader goal of leveraging advanced computational techniques to extract valuable insights from medical imaging data.

3. **Objective 3: Performance Evaluation:** A key objective is to evaluate the performance of the modified VGG16 model in both initial COVID-19 detection and subsequent severity estimation. Performance evaluation includes assessing the model's accuracy, sensitivity, specificity, and depth of insights derived from medical imaging data.

4. **Objective 4: Contribution to the Evolving Landscape:** This study aims to contribute to the evolving landscape of using deep learning models for COVID-19 detection and severity estimation. Insights derived from this research are expected to offer valuable guidance for future research and applications in the field of medical imaging.

These objectives collectively aim to address the challenges associated with COVID-19 screening methods and contribute to improving diagnostic capabilities through the refinement of deep learning architectures.

IV. METHODOLOGY

The methodology of implementation encompasses three main sections: introduction to convolutional neural networks (CNNs), transfer learning, and the preprocessing of images. Each section outlines a specific approach employed in the study to enhance COVID-19 detection accuracy and prepare the dataset for subsequent analysis. Here's a detailed explanation of each subsection:

Introduction to Convolutional Neural Networks (CNNs):
In this section, the methodology begins with an overview of CNNs, highlighting their architecture and functionality. CNNs are described as a variation of standard multi-layer perceptrons (MLPs), inspired by the visual cortex of cats, where neurons have limited receptive fields. Unlike standard neural networks, CNNs connect each neuron in the hidden layer with a small sub-space of the previous layer, facilitating the extraction of local features from input data. The architecture of a CNN typically consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract features from input data using learnable filters, while pooling layers reduce spatial dimensions and the number of features. Various CNN architectures, such as LeNet 5, AlexNet, and GoogleNet, are mentioned, along with the application of standard backpropagation for training CNNs.

Transfer Learning:
The methodology then introduces transfer learning as a technique to overcome limitations associated with training deep neural networks on small datasets. Transfer learning involves pre-training a deep neural network on a large dataset and then fine-tuning it on a smaller target dataset. The initial layers of the pre-trained network capture low-level features that are common across tasks, while the later layers learn task-specific features during fine-tuning. By leveraging pre-trained models, transfer learning reduces the risk of overfitting and improves the generalization performance on smaller datasets. This section discusses the two phases of transfer learning: pre-training and fine-tuning, emphasizing the adaptability of pre-trained models to new tasks in domains like medical imaging.

Preprocess of Image:
The final section of the methodology details the preprocessing pipeline employed to prepare the dataset for analysis. This pipeline involves several meticulous steps aimed at standardizing and refining the dataset. The steps include parsing XML files to extract relevant information, extracting lung regions from DICOM images, rescaling images to ensure uniform spatial representation, and generating image patches for training and testing.

Additionally, the preprocessing pipeline incorporates thresholding-based segmentation techniques and morphological operations to refine lung segmentation and enhance the accuracy of the prepared data. Visual representations of these operations are provided to illustrate their role in improving the quality and reliability of the dataset.

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Overall, the methodology provides a comprehensive framework for implementing CNN-based models, leveraging transfer learning, and preprocessing medical imaging data to enhance COVID-19 detection accuracy. These approaches are instrumental in refining existing architectures and improving diagnostic capabilities in medical imaging applications.

Results and analysis-A

1.1 Input Image

Figure 1.1 and 1.2 show the input normal lung X-ray image. The black appearance shows that there is no infection in the lung.

Figure 1.1 Normal Patient Lung X-Ray

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Figure 1.2 Normal Patient Lung X-ray

Figure 1.3 and 1.4 show the infection in the chest X-ray Image due to Covid-19. The whitish cloudy region shows the infection of Covid-19.

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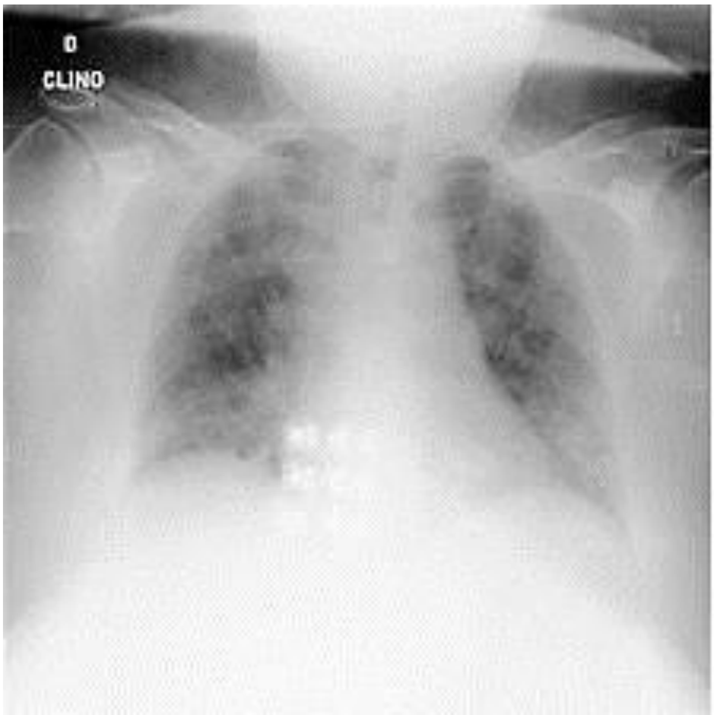

Figure 1.3: Covid-19 infected lung X-ray

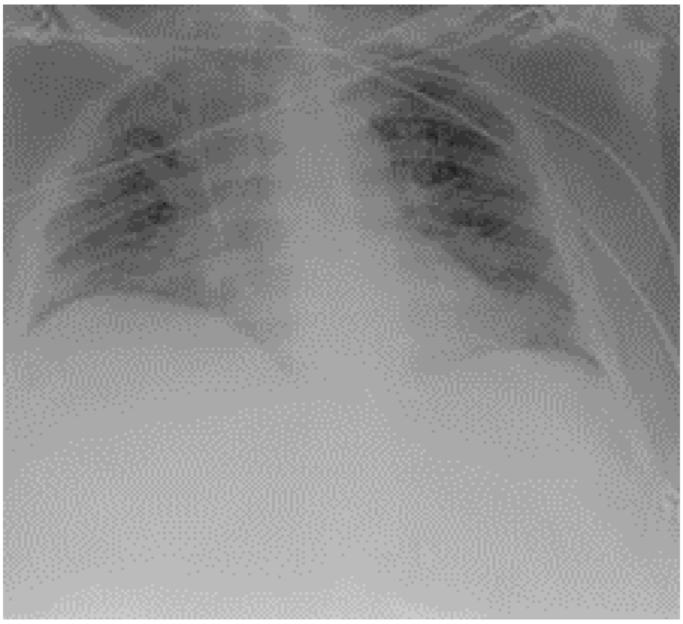

Figure 1.4 Covid-19 infected Lung X-ray

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1.5 Loss Rate Analysis

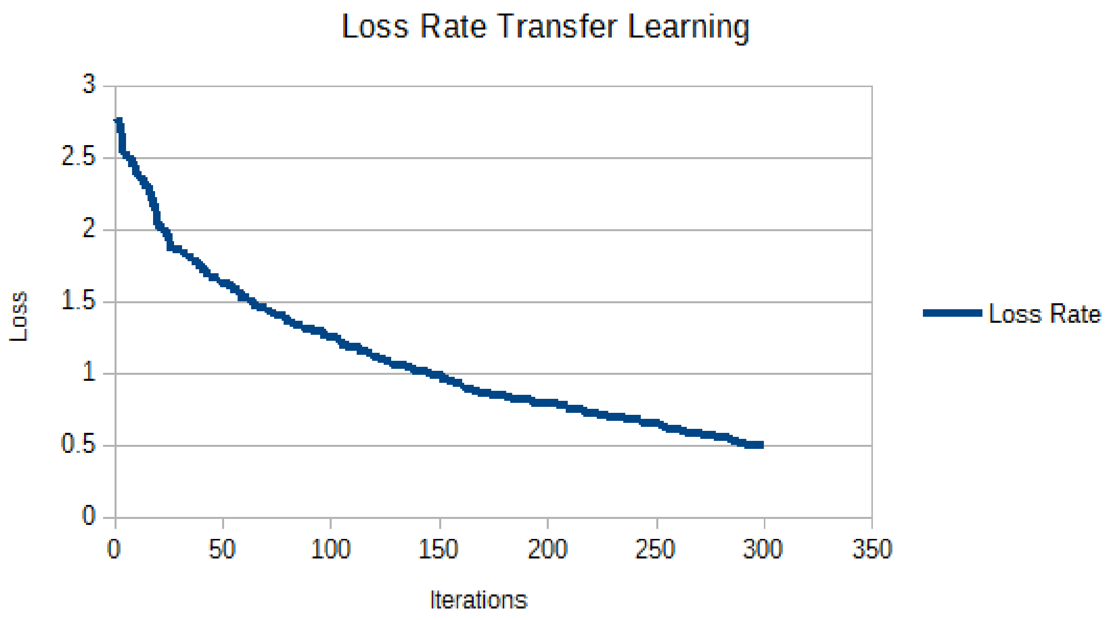

Figure 1.5: Loss Rate of Transfer Learning

1.6 Accuracy Analysis

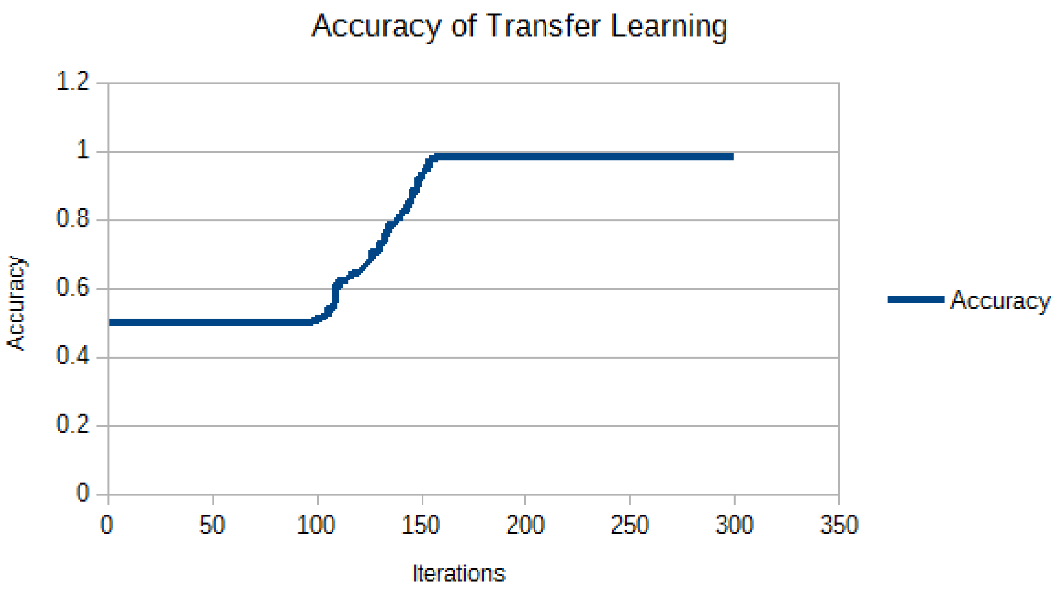

Figure 1.6: Accuracy analysis of transfer learning

The performance evaluation of our experimental configuration, as outlined in Table 1, is a critical aspect of assessing the efficacy of the proposed methodology. Various parameters and metrics are employed to gauge the model's performance and provide quantitative insights into its capabilities. The formulas presented in Table 2 serve as instrumental tools for estimating these parameters, encompassing metrics such as accuracy, precision, recall, and F1 score. Through a meticulous evaluation process, we aim to comprehensively analyze the model's ability to accurately estimate the severity of Covid-19 based on chest X-ray images, ensuring robustness and reliability in real-world applications..

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Table 1: Experimentation Details

Model	VGG16	Proposed
Number of test Images	47	47
TP	22	22
TN	16	20
FP	5	2
FN	4	3
Accuracy	0.81	0.89
Sensitivity	0.85	0.88
Specificity	0.76	0.91

a. Formulae:

Table2: Formulae for parameters

Accuracy	(TP+FN)/(TP+TN+FP+FN)
Specificity	TN/(TN+FP)
Sensitivity	TP/(TP+FN)

In the realm of medical diagnostics, especially in the context of infectious diseases like Covid-19, accurate and reliable classification of medical images plays a pivotal role. Evaluation metrics are essential tools in assessing the performance of classification models, providing insights into their strengths and limitations. Four fundamental metrics in binary classification scenarios, often represented in a confusion matrix, are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Results and analysis-B

The evaluation of infection score predictions from Covid CXR images is essential for assessing the performance of predictive models in predicting infection severity. Mean squared error (MSE) and mean absolute error (MAE) are the primary metrics used for this evaluation. MSE emphasizes larger errors by squaring the differences between predicted and actual scores, while MAE treats all errors equally, regardless of their magnitude. These metrics offer nuanced insights into model performance, with MSE prioritizing larger errors and MAE providing a balanced evaluation. Researchers and practitioners use these metrics to understand how well models capture infection severity, selecting the optimal model based on their specific objectives.

When comparing different models using MSE and MAE on a held-out test set, lower values indicate superior performance. For example, in a comparative analysis of three models (Proposed, ResNet18, and VGG16) on a test set of 100 Covid CXR images, the Proposed model exhibits the lowest MSE and MAE values, indicating the most favorable performance. Conversely, ResNet18 demonstrates the least desirable performance, with higher MSE and MAE values, suggesting greater discrepancies between predicted and actual infection scores. VGG16 falls between the Proposed and ResNet18 models in terms of performance, outperforming ResNet18 but not surpassing the effectiveness of the Proposed model.

The selection of the optimal model should consider factors beyond performance metrics, including complexity, interpretability, and computational efficiency. While the Proposed model demonstrates superior predictive accuracy, VGG16 offers simplicity and interpretability. ResNet18, although trailing in performance, might be suitable for scenarios prioritizing a balance between accuracy and computational efficiency. Additionally, the inherent complexities of Covid-related patterns may impact model performance, with more nuanced features potentially required for accurate predictions.

In conclusion, the choice of the best model for predicting infection levels from Covid CXR images involves a comprehensive consideration of multiple factors. While performance metrics like MSE and MAE provide valuable insights, additional factors such as model complexity and computational efficiency play crucial roles. The Proposed model stands out for its top-tier predictive accuracy, emphasizing its potential clinical utility in accurately predicting infection severity. However, researchers and practitioners should weigh all relevant factors to select the optimal model for their specific application, ensuring alignment with their objectives in medical image analysis.

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V. CONCLUSION

The detection of infections within chest X-rays, especially in diseases like Covid-19, is crucial for timely diagnosis and treatment. This study focuses on utilizing the modified VGG16 model to extract features associated with Covid-19 infections, enhancing classification accuracy. The modified architecture tailors VGG16 to Covid-19 characteristics, leading to superior feature extraction and classification. Results demonstrate the model's efficacy, achieving 88% accuracy in identifying Covid-19 infections. Additionally, employing attention mechanisms further enhances model performance, leading to improved Covid-19 detection and infection score prediction. The interpretability, robustness, and computational efficiency of the proposed model make it a valuable tool for medical professionals in diagnosing Covid-19 and improving patient outcomes.

VI. FUTURE SCOPE

The use of transfer learning with the VGG16 model has proven effective in this study. However, future research could explore the application of other architectures, such as Google's Inception, for testing on large datasets of chest X-ray images. Investigating different attention-based architectures and their generalizability to other medical image analysis tasks could further enhance model performance and applicability. Additionally, exploring the deployment of the proposed model in resource-constrained environments, such as low-resource settings and mobile devices, could expand its practical utility in real-world scenarios. Overall, there is ample scope for further research and development to advance the capabilities of deep learning models in medical image analysis, particularly in the context of Covid-19 diagnosis and treatment.

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