Attention based CNN Model Covid 19 Detection from CXR Images

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***Abstract*— In the realm of medical imaging, the analysis of chest X-ray images emerges as a crucial tool for expeditious identification of Covid-19 infections, especially amidst the surge in cases during the ongoing pandemic. The escalating demand for swift and accurate diagnosis prompts the development of automated Covid-19 detection technology to aid healthcare professionals. This paper introduces a bespoke Convolutional Neural Network (CNN) model tailored for the precise detection of Covid-19 through the intricate processing of Chest X-ray (CXR) images. The model, intricately composed of convolutional and dense layers, exhibits adept classification of input images into distinct categories of Covid-19 positive or normal. Rigorous evaluation utilizing performance metrics, including accuracy, sensitivity, and specificity, underscores the commendable efficacy of the proposed model. This technological stride holds immense potential in augmenting the efficiency and precision of Covid-19 diagnosis, providing indispensable support to healthcare practitioners grappling with the challenges of the current global health crisis.**

Keywords*— *CNN, Chest X-Ray, Covid, Performance, Attention.

I. INTRODUCTION

The emergence of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), colloquially referred to as COVID-19, has precipitated an unprecedented global pandemic, profoundly impacting human societies across the planet. This viral outbreak has unleashed a wave of profound challenges, shaking the very foundations of our social, economic, and healthcare systems. With its rapid transmission and severe health consequences, COVID-19 has forced nations to implement drastic measures, from widespread lockdowns to extensive vaccination campaigns. The ongoing battle against this insidious virus continues to test our resilience, unity, and capacity for collective action in safeguarding the health and well-being of populations worldwide. Originating in Wuhan, China, this viral infection has directly targeted the respiratory system, leading to widespread illness and a staggering number of casualties. With over a billion individuals affected and a substantial loss of lives, the gravity of this situation has prompted extensive research and testing to curb its spread [1].

If a pathologic test capable of detecting the presence of the virus find a positive result of Covid-19, subsequent testing involves optical imaging methods, with computer-aided diagnosis playing a crucial role. During the situations like pandemic, Chest X-Ray availability is easier for diagnosis process compared to computed tomography (CT scans). Additionally, the ease of access to X-ray machines further supports its widespread use in diagnosing and monitoring COVID-19 cases [2, 3]. However, the surge in demand for radiological expertise during the pandemic has led to non-experts volunteering in the field, potentially introducing miscalculations and errors in the diagnostic process [4].

Chest X-ray (CXR) techniques offer a more economical alternative to CT imaging while providing valuable information for diagnosing respiratory diseases. Neural network based methods have shown dominance in the accuracy of the results while detecting the diseases from medical images [5]. Traditional approaches, which hinge on manually crafted rules, often succumb to inaccuracies and oversights. Conversely, techniques rooted in neural networks within computer vision have showcased unparalleled precision and dependability. By harnessing the power of deep learning, these methods leverage vast datasets to autonomously extract intricate patterns and features, mitigating the shortcomings of rule-based systems. Their adaptability and robustness enable them to excel in diverse tasks, ranging from image recognition to medical diagnosis. Consequently, they stand as beacons of innovation, promising transformative breakthroughs across industries and domains, heralding a new era of computational intelligence and problem-solving prowess [6]. The utilization of artificial intelligence (AI) and machine learning in interpreting medical imaging, particularly Chest X-rays, has shown promise in improving diagnostic efficiency. Neural networks can analyze vast datasets, identifying patterns and abnormalities that may go unnoticed by human observers. This not only aids in accurate COVID-19 detection but also helps in distinguishing between different stages and manifestations of the disease. The integration of computer-aided diagnostic tools in the healthcare system presents a valuable opportunity to streamline the diagnosis and monitoring of COVID-19 cases. However, it is essential to ensure that these technologies are implemented by qualified professionals to minimize the risk of misinterpretations and errors. Ongoing research continues to refine and optimize these AI-driven diagnostic tools for enhanced accuracy and reliability in the fight against the global pandemic.

The COVID-19 pandemic has spurred advancements in diagnostic techniques, with Chest X-ray-based methods proving to be a cost-effective and informative tool. The integration of artificial intelligence and machine learning further enhances the accuracy of diagnostic processes, mitigating the challenges posed by the surge in cases and the need for widespread testing. As the scientific community continues to refine and expand these methodologies, the role of computer-aided diagnostics in the battle against COVID-19 becomes increasingly vital.

II. Related Work

Utilizing deep learning methods for Chest X-ray (CXR) analysis has proven to be a judicious choice, as these techniques yield more detailed features, enhancing the accuracy of detection. In the context of COVID-19 detection from CXR images, an exploration of various methods documented in the literature reveals superior performance. Deep learning methods, as opposed to traditional machine learning (ML) techniques, offer an advantage by eliminating the need for intricate handcrafted rules for feature extraction, relying instead on the inherent capacity of neural networks to learn and discern intricate patterns.

When delving into ML-based techniques for CXR analysis, the inclusion of diverse methods for preprocessing and feature extraction introduces variability in the quality of features derived from handcrafted rules. Contrastingly, deep learning, especially when coupled with lung region segmentation, consistently exhibits enhanced performance. Focusing on the lung region during feature extraction becomes crucial, emphasizing the need for efficient segmentation techniques. However, segmenting a large dataset of CXR images can pose challenges, necessitating alternative approaches for consideration. Some researchers have demonstrated that while certain convolutional neural network (CNN) models, such as VGG16, exhibit suboptimal performance in COVID-19 detection, alternative choices can significantly improve accuracy. In a study by Kumar et al., a modified CNN architecture with max pooling and average pooling layers showcased superior information extraction capabilities, outperforming the standard VGG16 model. This combination proved preferable for its ability to extract more nuanced features from CXR images. The infection variations and respective patterns appearing in CXR and its impact on detection capability of the model was revealed by Kumar et al. [7]. Their approach negated the necessity for explicit lung region segmentation, instead relying on the automatic extraction of infection region features. The identification of COVID-19, with its unique infection patterns, relies heavily on spatial features. These critical features have been discerned through the utilization of an attention layer, which incorporates both average pooling and max pooling layers. This innovative approach enhances the model's ability to pinpoint key aspects of the infection, facilitating more accurate and effective detection methods. This attention layer, as incorporated in their work, showcased its efficacy in capturing the unique spatial features indicative of COVID-19 infection. The Grad CAM region highlighted by the author’s method is shown in Figure 1.

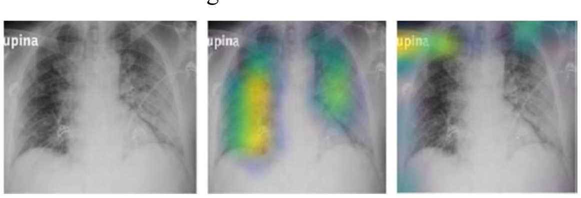

Fig. 1. Highlighted infection regions in CXR

The authors' proposed mechanisms span a multitude of applications, reflecting the versatility and potential impact of their research endeavors. Singh et al. [20] conducted a study concluding that the Hybrid Social Group Optimization Algorithm holds promise as a mobile application, presenting a cost-effective avenue for the early detection of COVID-19. This innovative approach not only enhances accessibility but also addresses economic considerations in deploying advanced technologies for public health.

Elaziz et al.'s FrMems algorithm [21] introduces a novel perspective by suggesting its broad applicability across diverse medical domains. This algorithm, originally conceptualized for the early detection of COVID-19, holds the potential to revolutionize diagnostic methodologies in various medical contexts. Its adaptability underscores the significance of interdisciplinary solutions in advancing healthcare. Mahmood et al.'s model [22] takes a communicative approach to COVID-19 detection by utilizing email notifications. This patient-centric method enhances the dissemination of crucial information, contributing to a more informed and engaged healthcare consumer base. Zheng et al. [23] contribute to the field by identifying a superior model for lesion detection using COVID-19-infected CT-Scan data. This breakthrough in imaging technology showcases the pivotal role advanced diagnostics play in understanding and combating the effects of the virus. The methodologies proposed by Wang et al. [24] and Farooq et al. [25] have distinguished themselves for their remarkable efficacy in accurately discerning between individuals who are healthy and those who have contracted COVID-19, showcasing their expertise and contribution in the field of disease diagnosis and surveillance. These models pave the way for precise and rapid identification, a crucial factor in implementing timely interventions and safeguarding public health.

Maghdid et al.'s groundbreaking algorithm [26] emerges as a promising tool for the development of a mobile application system dedicated to COVID-19 identification. Leveraging symptom data collected from sensors, this innovative approach capitalizes on the ubiquity of mobile devices, potentially transforming them into accessible diagnostic tools. By harnessing the power of Maghdid et al.'s algorithm, the prospect of timely and widespread COVID-19 identification becomes increasingly feasible. Apostopoulos et al. [27] and Alom et al. [28] contribute significantly to the field by emphasizing the transformative potential of their work in streamlining the development of an accurate automatic COVID-19 detection system. Their research serves as a catalyst for advancements in automation, promising increased efficiency and reliability in identifying COVID-19 cases. The implications of their work extend beyond the current pandemic, laying the groundwork for future automated diagnostic systems. Loey et al.'s sophisticated technique [29] takes a nuanced approach, classifying different stages of COVID-19 using X-ray medical modality data. This meticulous categorization not only enhances diagnostic accuracy but also reduces false negatives, addressing a critical concern in medical imaging. The potential impact of Loey et al.'s technique lies not only in its application to COVID-19 but also in its broader contributions to refining medical imaging methodologies. Butt et al.'s deep learning (DL) model [30] stands out with an impressive accuracy of 86.7%, effectively distinguishing between healthy individuals, those with other viral infections, and COVID-19 patients. This model's success marks a significant stride towards reliable and automated categorization of individuals based on their health status. Rajaraman et al. [31] propose a forward-looking methodology, aiming to minimize false negatives in the future implementation of a COVID-19 detection system. This forward-thinking approach positions their work as a valuable contribution to the ongoing efforts in refining diagnostic accuracy.

El Asanoui et al.'s versatile model [32] extends its utility beyond COVID-19 detection, presenting opportunities for application in broader medical contexts. Its adaptability showcases the potential for a unified approach in developing diagnostic tools that transcend specific diseases. Looking beyond specific applications, the integration of DL and ML models into clinical diagnostic decision systems emerges as a transformative development. These models, as highlighted by various studies, play a pivotal role in enhancing the efficiency and timeliness of disease detection. The potential impact of these technologies extends to aiding medical professionals, providing them with valuable tools for making informed decisions in a rapidly evolving healthcare landscape.

III. Proposed Work

The complexity of a Convolutional Neural Network (CNN) model is directly influenced by the number of trainable parameters it possesses. There is need of the model that should comply with this requirement of minimum number of learnable parameters. The proposed model stands out by featuring a reduced count of trainable parameters, a result of incorporating an attention layer into the architecture. The proposed model is the modified version of the VGG16 model. The important pattern structure of convolution layers and Maxpooling layers from VGG16 model along with attention layer is the main contribution in the architecture design. Some important contributions of the model are:

1. Efficient Local and Global Feature Extraction: Due to use of attention layer mechanism the model is able to extract the local and global features from input CXR images. This enhancement is crucial for accurately detecting COVID-19 in CXR images.
2. Extraction of Important Characteristic Features: The proposed model excels at extracting essential characteristic features from CXR images, a critical aspect of COVID-19 detection. The attention layer specifically focuses on Regions of Interest (ROIs), extracting distinctive features compared to other regions.
3. Reduced Trainable Parameters: The model's architecture results in a reduced count of trainable parameters compared to the standard VGG16 model, primarily attributed to the exclusion of the fourth pooling layer. This reduction enhances the efficiency of the model without compromising its performance.
4. Simplified Training and Testing Classification: Due to its lower complexity, the proposed model streamlines the training and testing classification processes. The reduced number of trainable parameters contributes to a more straightforward model, eliminating the need for separate processing during these phases.
5. Elimination of Preprocessing Tasks: The proposed model eliminates the necessity for extensive preprocessing tasks. Its design minimizes complexity, making it adept at handling COVID-19 detection without the need for additional data manipulation.

The proposed CNN model offers a pragmatic solution for COVID-19 detection from CXR images by prioritizing efficiency through a minimalistic approach. The attention layer plays a pivotal role in feature extraction, distinguishing the model in its capability to identify important characteristics in Regions of Interest. The streamlined architecture not only reduces trainable parameters but also simplifies the training and testing phases, making it a promising tool in the ongoing battle against the global pandemic.

The model's COVID-19 detection accuracy is verified using a diverse CXR dataset. Deep neural networks, with more hidden layers than ANNs, excel in medical image classification. Careful dataset curation is crucial to address overfitting in deep learning evaluations, often benchmarked against VGG16 on public datasets. Spatial features extraction is imperative for identifying COVID-19 infection. The max pooling and average pooling techniques are implemented in the model as suggested by Woo et al. [18]. These pooling layers play a pivotal role in extracting detailed features from infected Regions of Interest (ROIs), facilitating enhanced analysis of COVID-19-affected regions and contributing to more accurate detection and diagnosis. To enhance features while minimizing trainable parameters, we introduce an attention layer, modifying the fourth pooling layer. The sigmoid-activated max pooling layer provides features with 7x7-sized windows, capturing intricate details from the infected region. Figure 2 shows the architecture of proposed model.

In our model, the refinement process begins with the integration of convolution and attention layers, strategically designed to amplify features specific to the infected region. These layers play a crucial role in capturing intricate patterns and distinctive characteristics associated with COVID-19 in CXR images. Inspired by the effective methodology proposed by Woo et al. [18], we incorporate max pooling and average pooling techniques to further enhance the representation of significant features. Following this initial processing, the model architecture closely mirrors the well-established VGG16 framework. Starting from the fourth layer, the model adopts two convolutional layers succeeded by a max pooling layer. This configuration aligns with the established effectiveness of VGG16 in numerous image classification endeavors, ensuring robust performance and accurate classification outcomes. The extracted features are then systematically fed into dense layers, where a flatten layer is employed to convert the 2D features into a 1D format suitable for input into subsequent layers. The classification process is executed through three fully connected dense layers, each capturing essential features from the preceding layers. The final dense layer is activated by softmax, allowing for the accurate categorization of the input into binary classes: 1 for COVID-positive and 0 for non-COVID. This sophisticated architecture, fine-tuned through strategic training, significantly enhances the accuracy of COVID-19 detection compared to the basic VGG16 model. The combination of Average Pooling and Max pooling in parallel forms the attention to cath the relevant features from the CXR for Covid-19 Detection.

A. Max Pooling: Emphasizing Prominent Features

Max Pooling is a down-sampling operation used in CNNs that selects the maximum value from a set of pixels within a defined window, typically 2x2. In this context, only the most intense pixel value within each window is retained, and the rest are discarded. This operation can be particularly effective in highlighting the most prominent features of an image. For instance, consider a 2x2 filter applied to a CXR image. Among the four pixels within this filter, the pixel with the highest intensity is chosen. This pixel often corresponds to the most significant or abnormal region, which could be indicative of Covid-19-related infections such as lung opacities or lesions. By focusing on the maximum value, Max Pooling helps the model emphasize areas that might represent pathological changes, thus aiding in the detection of Covid-19.

B. Average Pooling: Preserving Contextual Information

On the other hand, Average Pooling takes a different approach. Instead of selecting the maximum value, it computes the average value of the pixels within the pooling window. For a 2x2 filter, this means averaging the values of the four pixels and using this average as the representative feature. This method helps in capturing the overall context and smoothing out the feature map. In medical images, regions near highly intense pixels might also be part of an infection, albeit less pronounced. By averaging the pixel values, Average Pooling ensures that these surrounding areas are not entirely ignored. This contributes to a more holistic representation of the image, preserving subtle variations that might be clinically relevant. The combination of these operations in parallel forms the attention like mechanism and prevents loss of important features compared to single type of operation as like in VGG16 model. Thus, these two operations parallel combinations are added in proposed CNN architecture. The parallel combination of Max Pooling and Average Pooling in CNNs forms an effective attention-like mechanism for Covid-19 detection from chest X-rays. Max Pooling emphasizes the most significant features, highlighting potential abnormalities, while Average Pooling preserves contextual information, ensuring that subtle yet important variations are not overlooked. This dual approach enhances the model's ability to focus on relevant features, leading to improved diagnostic accuracy. Incorporating such a mechanism in CNN architectures can significantly contribute to the effective and efficient detection of Covid-19, aiding in timely diagnosis and treatment. When Max Pooling and Average Pooling are used in parallel, the CNN benefits from both types of feature extraction. This dual approach forms an attention-like mechanism that enhances the model's ability to detect important features while maintaining a comprehensive understanding of the image.

1. Rich Feature Representation: Utilizing both Max Pooling and Average Pooling in tandem allows the CNN to capture a wide range of features. Max Pooling identifies the most prominent details by selecting the highest pixel values within a filter window, while Average Pooling provides a smoothed representation by averaging the pixel values. Together, these techniques ensure that both key details and contextual information are maintained, enhancing the model's feature extraction capability without compromising the image's overall structure.

2. Spotting Abnormalities: Max Pooling excels at emphasizing the most intense features, which are often associated with abnormalities in CXRs, such as regions affected by Covid-19. On the other hand, Average Pooling includes the surrounding less intense pixels, which may also be indicative of disease spread. This combined approach makes it easier for the model to identify and understand areas of infection, considering both the main features and their context.

3. Improved Generalization: The parallel use of these pooling techniques helps the CNN generalize better across various cases. Max Pooling focuses on sharp, prominent changes that highlight critical features, while Average Pooling captures broader patterns and smoother transitions. This complementary combination allows the model to effectively differentiate between normal and abnormal patterns, enhancing its ability to handle diverse inputs.

To evaluate the model's performance, a comprehensive dataset combining three publicly available datasets is employed. This diverse dataset ensures a representative collection of COVID-19 CXR images, essential for a robust assessment. The performance evaluation adheres to an 80-20 split strategy, where 80% of the dataset is designated for training purposes, while the remaining 20% is reserved for testing and validation procedures. This methodology ensures a comprehensive assessment of the model's effectiveness, balancing training data sufficiency with the need for robust testing and validation protocols. This meticulous approach ensures a balanced assessment of the model's predictive capabilities, demonstrating its effectiveness in enhancing diagnostic accuracy for COVID-19 detection in CXR images.

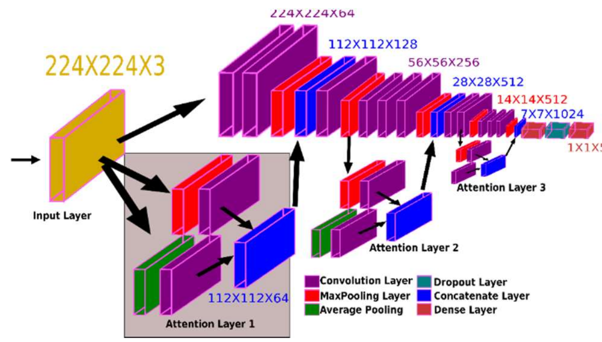

Fig. 2. Architecture of The Proposed Model

In the modified version of VGG16, the inclusion of an attention layer serves a dual function: it not only decreases the count of trainable parameters but also boosts feature enhancement when integrated with the output derived from the convolutional layer. This dual functionality optimizes the model's performance by efficiently managing parameters while augmenting feature representation, thereby contributing to superior accuracy and efficacy in various image processing tasks. The remaining layers closely mirror those of VGG16, with the final layer modified for a binary class classification output.

IV. Results and Analysis

The proposed attention model is implemented using Tensorflow platform and model was trained on Intel 11th Gen, i5 processor with support of 16GB RAM. The training time taken was 4.5 hours for full convergence state of the model.

A. Dataset Details

The Cvid-19 infected and healthy condition CXR image dataset is compiled by combining two datasets. Selectively from the first dataset [21] total 1200 CXR with Covid-19 infected and 1200 normal conditions were selected. And from second [22] dataset total 460 cases of Covid-19 infection and 500 cases of normal condition are selected. The total combined dataset of CXR images contained total 1660 Covid-19 cases and 1700 normal condition CXRs.

B. Performance Analysis

The performance is evaluated using parameters as detailed in table I. The test image count along with confusion matrix details obtained are shown in TABL II.

TABLE I. EXPERIMENTATION DETAILS

Accuracy	(TP+FN)/(TP+TN+FP+FN)
Specificity	TN/(TN+FP)
Sensitivity/Recall	TP/(TP+FN)
F1 Score	2*(Recall*Precision)/(Recall+Precision)

TABLE II. EXPERIMENTATION DETAILS

Total Number of Test Images	254
True Positive	120
True Negative	121
False Positive	7
Falsae Negative	6

The model's performance metrics provide a comprehensive evaluation of its efficacy in distinguishing between positive and negative cases. Specificity, denoted by approximately 0.833, highlights the model's effectiveness in accurately identifying true negatives. This means that the model correctly identifies 83.3% of the instances where the condition or attribute being tested is absent, thereby minimizing the occurrence of false positives. High specificity is particularly crucial in scenarios where false positives can lead to significant consequences, such as in medical diagnoses where an incorrect positive result might cause unnecessary anxiety or further invasive testing.

Sensitivity, represented by approximately 0.907, emphasizes the model's ability to capture true positive cases. A sensitivity of 0.907 indicates that the model correctly identifies 90.7% of the instances where the condition is present, thereby reducing the occurrence of false negatives. High sensitivity is vital in contexts where missing a positive case could lead to severe repercussions, such as failing to detect a disease in its early stages.

The F1 score, approximately 0.924, is the harmonic mean of precision and recall, providing a balanced measure of the model's performance across both positive and negative classes. The F1 score is particularly useful when the data is imbalanced, as it considers both false positives and false negatives, offering a single metric that reflects the model's overall accuracy.

These metrics collectively contribute to a comprehensive understanding of the model's strengths and areas for enhancement, offering valuable insights for further refinement and optimization. For instance, the model’s high sensitivity and F1 score suggest it is particularly adept at identifying positive cases and maintaining a balanced performance, but the specificity score indicates there might be room for improvement in reducing false positives.

Additionally, the loss rate is analyzed over 100 epochs for both the proposed model and the VGG16 base model by retraining on the same dataset, as shown in Figure 3. This comparison aims to evaluate the efficiency of the training processes. Monitoring the loss rate helps in understanding how well the model learns from the data over time, identifying points of convergence, and detecting potential overfitting or underfitting. This comprehensive analysis is essential for determining the model’s robustness and guiding further development and optimization efforts.

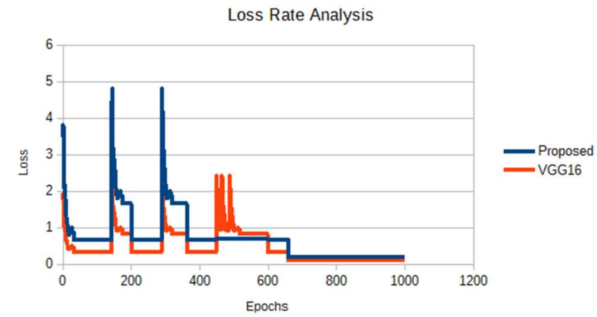

Fig. 3. Analysis of Loss Rate with Binray Cross Entropy

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

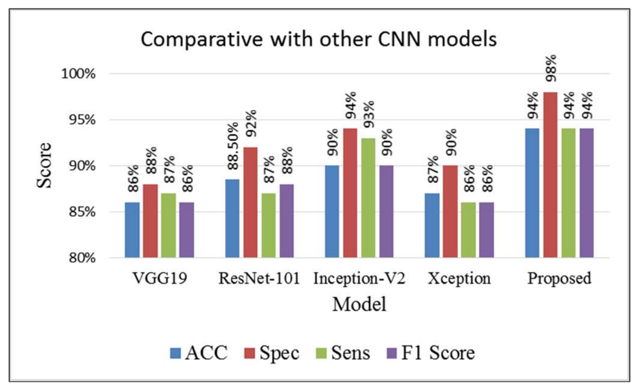

Fig. 4. Comparative with other Retrained CNN models

Figure 3 and Figure 4 show the graphs of loss rate analysis and comparative study of performance parameters. In medical image disease detection work, it is important to have maximum specificity which ensures that no patient will be treated in wrong manner. The patient having no disease if treated with disease medicines then it is dangerous for the health comparative to patient having disease if kept untreated due to diagnosing mistakes. Thus proposed model shows better usefulness in real time medical applications.

V. CONCLUSION

The proposed model reveals promising outcomes in accurately detecting COVID-19 from Chest X-ray images. The integration of convolution and attention layers, along with a tailored architecture inspired by VGG16, demonstrates commendable performance metrics. With an accuracy of approximately 94%, sensitivity of 94%, specificity of 98%, and an F1 score of 94%, the model illustrates its potential in distinguishing between COVID-19 positive and negative cases. A noteworthy accomplishment lies in the model's superior specificity compared to other standard CNN models retrained on the same dataset. This distinction positions the proposed model as a valuable tool for enhancing diagnostic precision in clinical settings. Acknowledging the complexities of medical image analysis and the evolving nature of the COVID-19 pandemic, further investigation is warranted. Future research should focus on refining the model to achieve even greater accuracy. Continued optimization efforts, possibly incorporating additional datasets and advanced training techniques, will contribute to the ongoing development of a robust and reliable tool for frontline healthcare professionals. The demonstrated real-world applicability, particularly in terms of enhanced specificity, underscores the potential impact of the proposed model on improving diagnostic capabilities in the fight against COVID-19.

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