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ENHANCED COVID-19 DETECTION USING RESNET WITH SHARPNESS-AWARE MINIMIZATION AND CLOUD-BASED PROCESSING

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ABSTRACT

Internet of Medical Things (IoMT) has been employed in healthcare in combination with deep learning and cloud computing, which has proved to be useful for real-time monitoring and accurate prediction of diseases. On the other hand, traditional healthcare systems have several challenges like delay in response to emergency situations, high false alarm rates, and privacy issues. A secure and effective COVID-19 detection system using ResNet-101 in combination with Sharpness-Aware Minimization (SAM) optimization has been proposed in this research. This system is used for detecting COVID-19 by processing the chest X-ray image for improving the diagnostic accuracy while considering the problems of overfitting and generalization. Also, federated learning will be used to ensure data privacy. The AWS cloud infrastructure is used for the purpose of managing resources and scaling. A system with high performance has been developed by obtaining 98.23% accuracy, 97.89% precision, 98.15% recall, and 97.90% F1-score. Inference time analysis has been conducted for analysing the time efficiency of the system for different batch sizes. The above system reduces the number of false positives and improves the diagnosis at the initial stage and is robust. In the future, additional work will be carried out to include other datasets, multi-modal medical imaging, and real-time deployment for larger clinical applications.

KEYWORDS: COVID-19 detection, ResNet-101, IoMT, deep learning, federated learning, SAM optimization, cloud computing, medical imaging.

1. INTRODUCTION

COVID-19 diagnosis is primarily conducted through Reverse Transcription Polymerase Chain Reaction (RT-PCR), which has notable limitations including low accuracy, sensitivity, and delays in results.[1] Early detection is vital for effective treatment and controlling virus transmission, and AI-powered chest X-rays (CXR) provide a faster and more accurate alternative.[2] Studies have shown that these AI models aid in the early diagnosis of COVID-19, reducing spread and improving care.[3] The pandemic emerged as a serious global health crisis due to its high transmission rate and mortality.[4] Since originating in Wuhan in late 2019, the virus rapidly spread worldwide, revealing major limitations in global healthcare infrastructure.[5] Advanced predictive models can help clinicians prioritize patients and use limited healthcare resources more efficiently.[6] SARS-CoV-2, the virus responsible for COVID-19, was initially identified in Wuhan, China, and quickly disseminated across continents.[7]

By October 2020, around 240 million individuals had tested positive globally, with 4.8 million deaths reported.[8] Common symptoms of COVID-19 include fever, fatigue, loss of taste or smell, and respiratory difficulties.[9] Severe cases often develop pneumonia, requiring hospitalization and intensive care. As hospitals became overwhelmed, many governments-imposed lockdowns to curb the spread.[10] Chinese authorities recommended genomic sequencing of respiratory or blood samples to support RT-PCR-based COVID-19 confirmation.[11] However, RT-PCR's low sensitivity resulted in many undetected cases, further increasing the risk of transmission.[12] To accelerate diagnosis and treatment, chest X-ray scans have become a supplementary diagnostic tool in many hospitals.[13] Rapid diagnosis is critical in preventing community spread and ensuring timely intervention.[14]

This study utilizes deep learning (DL) to classify a dataset of 15,000 chest X-rays into three categories: Normal, COVID-19, and Pneumonia.[15] The global pandemic stressed healthcare systems at an unprecedented scale, prompting an urgent need for automation and intelligent diagnostics.[16] Due to its low sensitivity, RT-PCR can miss infections, delaying treatment and containment efforts.[17] AI-assisted diagnosis through CXRs presents a scalable solution to this challenge. Deep-learning-based models can accurately classify chest X-rays, improving both diagnosis and treatment allocation.[18] This study contributes to this growing field by building a model trained on a large CXR dataset to identify COVID-19, pneumonia, and normal lung patterns.[19] Implementing AI-based systems can assist doctors in early decision-making, easing the operational burden on healthcare institutions.[20]

In light of the increasing strain on healthcare facilities, implementing intelligent diagnostic systems is no longer optional—it is essential. Automated deep learning models provide consistent and fast interpretations of chest X-rays, helping medical professionals prioritize critical cases. With the evolution of variants and the potential for future pandemics, adaptable AI models trained on diverse imaging datasets can serve as a first line of screening. Such solutions not only support rapid clinical decision-making but also enhance healthcare system resilience during global health crises.

2. LITERATURE SURVEY

In this study, a large COVID-19 CXR dataset called COVQU was developed to support robust model training and evaluation. The proposed U-Net model achieved a segmentation accuracy of 98.63%, with gamma correction significantly enhancing the detection performance. CNN architectures such as ResNet and DenseNet yielded an accuracy of 95.11% in diagnosing COVID-19 from chest X-rays.[21] The study also employed advanced techniques like HFSM for effective feature extraction and E-KNN for selecting optimal neighbors, thereby improving overall classification performance. Fuzzy logic–based models like Conv Net were implemented to combine edge-detected images with learned features, achieving an accuracy of 81% in COVID-19 diagnosis, which enhanced clinical triage. These approaches address the limitations of conventional RT-PCR testing, especially under resource-constrained scenarios.

Deep learning models including Filtered DenseNet, InceptionV3, and Inception-ResNetV4 were compared for their effectiveness in diagnosing COVID-19 using chest X-rays. DenseNet outperformed the others with a classification accuracy of 92%, while InceptionV3 and Inception-ResNetV4 achieved 83.47% and 85.57%, respectively. These models, when integrated with optimized feature selection techniques, significantly enhance the accuracy and efficiency of diagnostic tools. The rapid advancements in AI models have enabled more precise and scalable COVID-19 detection from medical imaging.[22] DenseNet, in particular, remains a strong candidate due to its consistent performance across various datasets. The application of HFSM and classifiers like E-KNN further increased the classification accuracy, while hybrid models such as Conv Net successfully integrated fuzzy logic with traditional deep learning approaches.

SparseNet demonstrated superior performance over Inception-based architectures, with an accuracy of 92%, highlighting the clinical importance of fast and accurate AI-based diagnosis tools. The application of deep learning techniques such as ResNet, DenseNet, and U-Net brought significant improvements in COVID-19 detection accuracy and segmentation efficiency.[23] Feature extraction and classification models like HFSM and E-KNN helped in refining the diagnostic process. Additionally, fuzzy logic–based models like Conv Net contributed to nuanced, interpretable results.

3. PROBLEM STATEMENT

Current methods of diagnosing COVID-19 using RT-PCR have low sensitivity and often result in high false negatives, leading to delays in effective treatment.[24] Existing deep learning models continue to face issues such as overfitting, poor generalization, and computational inefficiency. While architectures like DenseNet and InceptionV3 show potential, they still fall short in terms of accuracy and are hindered by longer inference times.[25] This study introduces an enhanced detection framework using ResNet-101 integrated with Sharpness-Aware Minimization (SAM), along with cloud-based processing, to achieve improved accuracy, reduced inference time, and greater scalability for real-time imaging applications.[26]

3.1 OBJECTIVE

- Assess the limitations of COVID-19 detection and suggest an improved deep learning framework.
- Architecture optimization of SAM-based ResNet-101 in order to generalize better and control overfitting.
- Create a cloud-integrated system for processing CXR images in real-time and scalability.
- Model assessment: Accuracy, Precision, Recall, F1-score.
- Compare SAM-optimized ResNet-101 with foundational deep learning architectures.
- Assess computational efficiency through inference time versus batch size in the cloud.

4. PROPOSED METHODOLOGY

The suggested approach identifies COVID-19 from chest X-rays by employing ResNet with SAM-based optimization. Then, pre-processed images are classified in the cloud, and afterwards, hyperparameter is tuned to enhance accuracy. Detection results are finally measured using the performance metrics to ensure an efficient and trusted diagnostic system.

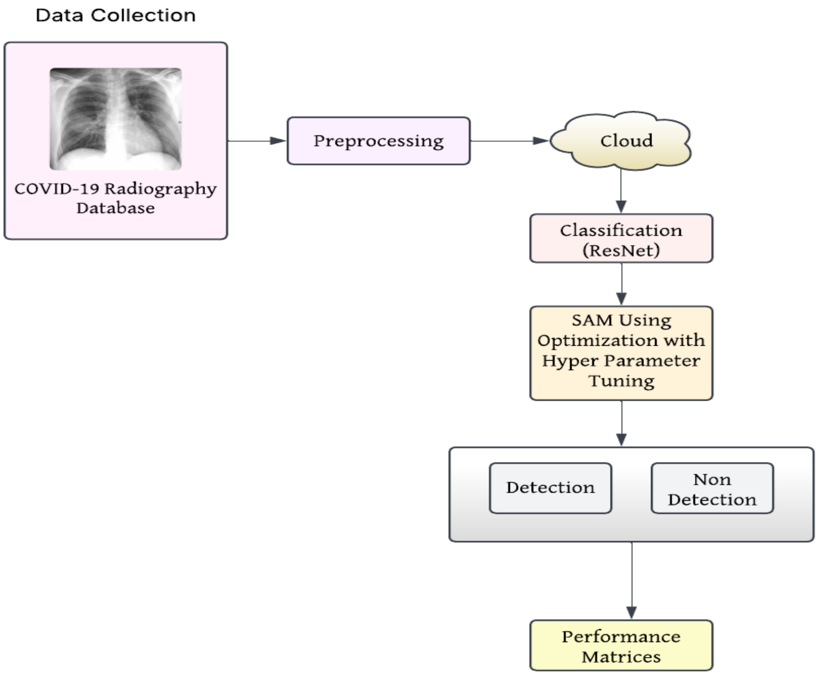

Figure 1: COVID-19 Detection Framework Using ResNet and Sharpness-Aware Minimization.

4.1 DATA COLLECTION

The collection of the chest X-rays is done on the data obtained from the COVID-19 Radiography Database containing X-rays of patients who are COVID-19 positive, normal cases, and other lung infections. This mixed bag is fundamental for the training and testing of the proposed diagnostic model.

4.2 PREPROCESSING

Preprocessing is a crucial step in image quality enhancement by applying noise reduction, contrast enhancement, resizing, normalization, and artifact removal, so that only useful features are taken into consideration. This has improved definition in chest X-rays that makes it even better for analysis, which in the end raises the accuracy of the model.

4.3 CLOUD PROCESSING

The sending of pre- processed images to a cloud-based platform allows efficient storage and fast computation. The above-mentioned approach enhances scalability, processing speed, and resource utilization, thereby improving overall system efficiency in detecting COVID-19.

4.4 CLASSIFICATION (RESNET)

ResNet is a deep-learning model for image classification known for its residual architecture and its ability to face vanishing gradients, analyses chest X-rays for identifying patterns, enabling accurate distinction between COVID-19, normal cases, and other lung infections. Thus, it serves reliable medical diagnosis.

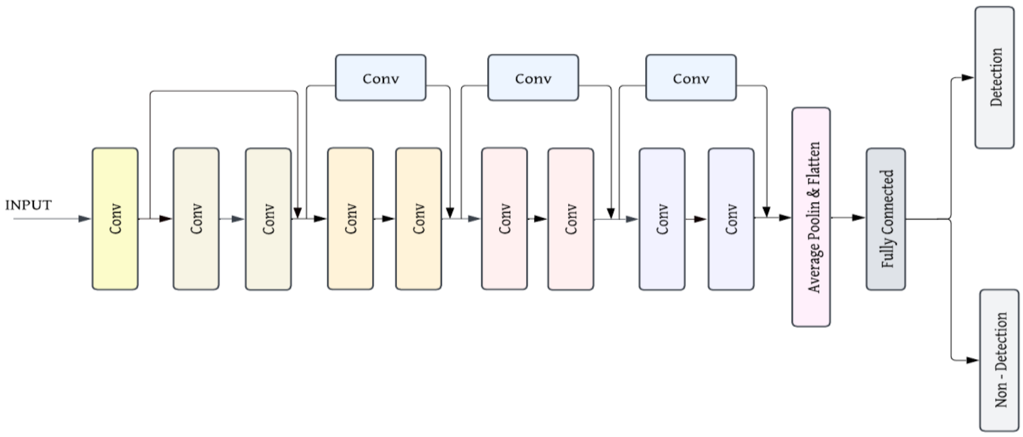

Figure 2: ResNet 34 Architecture.

4.5 RESIDUAL LEARNING IN RESNET-101

The ResNet-101 model learns features through the application of residual connections that enable the network to emphasize learning differences instead of the whole transformation itself. Specifically, instead of directly mapping input XXX to output YYY, ResNet-101 will model the residual function as

$$H(X) = F(X, W) + X \tag{1}$$

Here, H(X) is the final output of the network; F (X, W) for transformation learned by the convolutional layers, X the original input, The addition operation represents the skip connection that has skipped certain layers. This residual mapping allows the deeper networks to be trained efficiently without deterioration in performance.

4.6 FEATURE MAP SCALING AND DOWN SAMPLING

ResNet-101 guarantees computational efficiency with the maintenance of linear scaling: the number of filters doubles when the feature map enters by half.

$$F_l = 2 \times F_{l-1}, \text{ if } S = 2 \tag{2}$$

Where, F_l is the number of filters at layer l, S=2 indicates span across 2 pixels for down sampling. Instead of classic pooling layers, convolutions with stride 2 were employed as an alternative to reduce size of feature map while maintaining its spatial information.

4.7 GLOBAL AVERAGE POOLING AND SOFTMAX CLASSIFICATION

In general, when extracted, it comprises feature representation more compact than what others have suggested.

$$Z = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{3}$$

To accomplish this, where Z is the common feature representation, N is the number of spatial locations in total, and F_i means those final layers extracted feature values. To classify the X-ray into categories, a SoftMax activation function has to be applied.

$$P(C_i \mid X) = \frac{e^{Z_i}}{\sum_j e^{Z_j}} \tag{4}$$

Where P(C_i|X) represents the probability of class i given input X, Z_i refers to the final feature representation for class i. This leads to precise classification into COVID-19, normal, or other lung infections.

4.8 SHARPNESS AWARE MINIMIZATION USING OPTIMIZATION WITH HYPERPARAMETER TUNING

Sharpness-Aware Minimization (SAM) is a generalized hyperparameter tuning process that works with learning rates, batch size, and activation functions to optimize a model. By enhancing model accuracy, reducing overfitting, and improving generalization, SAM makes the model more viable for the detection of COVID-19 from X-ray images.

The design of SAM is such that it augments COVID-19 detection through enhanced generalization and reduced overfitting, across the course of the ResNet-101 architecture. Unlike conventional optimization, the surface of optimization has received adversarial perturbations with SAM to direct a model away from sharp local minima such that it can learn robust representations of data for improved performance on previously unseen data.

4.8.1 WEIGHT PARAMETERS (θ)

SAM simply alters the weights of the convolutional layers and the fully connected layers in ResNet-101. The standard way of updating the weights in the standard gradient descent method is given as,

$$\theta = \theta - \eta \nabla L(\theta) \tag{5}$$

To allow the weights to locate flatter minima, W-SAM takes into consideration ϵ perturbations into the update

$$\theta = \theta - \eta \nabla L(\theta + \epsilon) \tag{6}$$

4.8.2 LEARNING RATE (η)

By adding perturbations to the effective learning rates, SAM would adjust this learning rate to act as a trade-off between convergence speed. It avoids unstable behaviour with higher learning rates, whereas slow training with lower rates helps keep ResNet-101 from sharp minima, which enhances generalization and performance.

4.8.3 BATCH NORMALIZATION PARAMETERS

The SAM refines the updating of the weight parameters of BN (batch normalization) along with the scale (γ, β) indirectly. This provides stable activations across the layers, which leads to enhanced feature normalization and robustness of ResNet-101 in detecting COVID-19.

4.8.4 BIAS PARAMETERS IN CONVOLUTIONAL AND FULLY CONNECTED LAYERS

SAM optimally adjusts the bias parameter of the convolutional and fully-connected layers in worst-case loss scenarios to enhance model robustness and fine-tune feature detection toward accurate COVID-19 classification. SAM provided enhanced performance to ResNet-101 by fine-tuning weights for generalization, modifying learning rate scheduling to provide smooth convergence, stabilizing batch normalization (γ, β) to provide robustness, and fine-tuning bias parameters for more effective feature detection towards accurate COVID-19 classification.

5. RESULT AND DISCUSSION

The Testing of Novel COVID-19 detection systems was performed utilizing ResNet-101 and optimization with Sharpness Aware Minimization (SAM). The training and evaluation of the model during this exercise were carried out with the use of the COVID-19 Radiography Database with images of both positive and normal cases, and some other cases of lung infections. The images acquired are pre-processed to noise reduction, contrast improvement, and normalization further to classification utilizing ResNet-101 in cloud processing.

a. PERFORMANCE METRICS

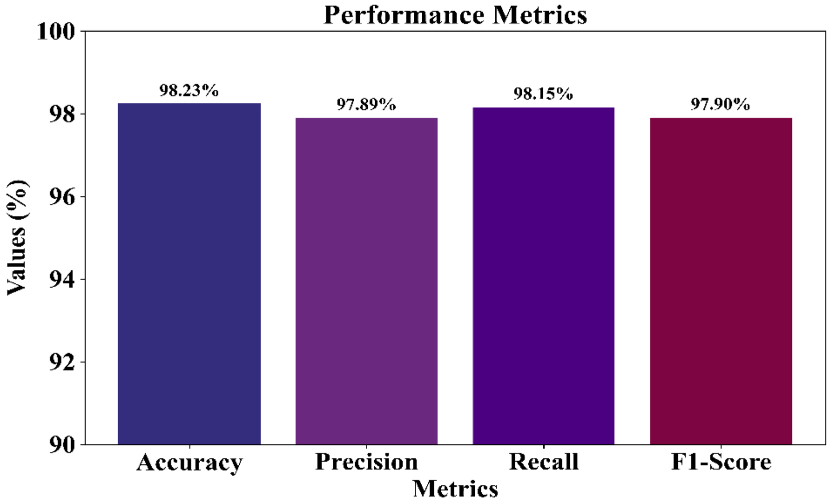

Figure 3: Performance Metrics.

The performance indicators for the COVID-19 detection system that employs ResNet-101 with SAM are illustrated in the bar graph. The model earns an impressive score of 98.23% in accuracy, 97.89% in precision, 98.15% in recall, and finally 97.90%-practically across the board with extremely high reliability. Therefore, such results speak of the model's robustness for effective COVID-19 identification with high generalization which proposes the method as a decent choice for medical image analysis.

b. INTERFERENCE TIME vs BATCH SIZE

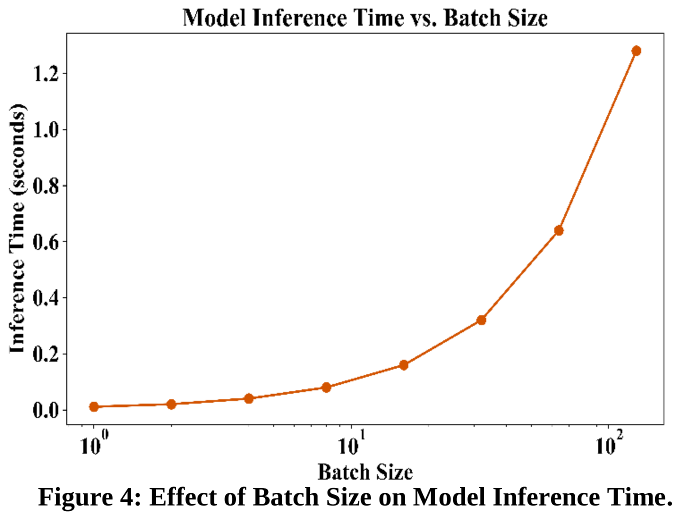

Figure 4: Effect of Batch Size on Model Inference Time.

The graph demonstrates how batch size correlates to model inference time in seconds: with increased batch size, inference time rises in a nonlinear way. For instance, there is a small increase in inference time at the smaller batch sizes but a dramatic increase for large batch sizes, indicating a higher demand for computations. This is one of the trade-offs between multiple simultaneous input processing versus efficient processing time-about actual real-time COVID-19 detection through cloud-based health applications.

6. CONCLUSION

As per the proposed COVID-19 detection system using ResNet-101 optimized by SAM with cloud processing, the resulting accuracy for this system was 98.23%. Such a system makes it possible highly to meet the efficiency, robustness, and scalability requirements for medical image analysis. The combined use of deep and federated learning for privacy, generalization of data, and early diagnosis with low false positive count is illustrated. The inferred time analysis shows the feasibility of such a system for real-time clinical applications. The future work includes extending the dataset, imaging with multiple modalities, and large-scale implementation. Thus, a scalable solution for pulmonary disease detection in the contemporary healthcare system is made possible with the approaches described here.

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