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Covid-19 Classification using Convolutional Neural Networks Based on Adam, RMSP, and SGD Optimalization

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Abstract - In this comprehensive study, a meticulous analysis of the application of Convolutional Neural Network (CNN) methodologies in the classification of Covid-19 and non-Covid-19 cases was conducted. Leveraging diverse optimization techniques such as RMS, SGD, and Adam, the research systematically evaluated the performance of the CNN model in accurately discerning intricate patterns and distinct features associated with Covid-19 pathology. the implementation of the RMS and Adam optimization methods resulted in the highest accuracy levels, with both models achieving an impressive 98% accuracy in the classification of Covid-19 and non-Covid-19 cases. Leveraging the robust capabilities of these optimization techniques, the study successfully demonstrated the effectiveness of the RMS and Adam models in enhancing the precision and reliability of the Convolutional Neural Network (CNN) for the accurate identification and differentiation of Covid-19 patterns within the medical imaging datasets. The notable achievement of 98% accuracy further emphasizes the potential of these optimization methods in advancing the capabilities of CNN-based diagnostic tools, thus contributing significantly to the ongoing efforts in Covid-19 diagnosis and management.

Keywords – Covid Classification, Adam, RMSP, SGD, CNN

1. INTRODUCTION

COVID-19 is an infectious disease caused by the novel coronavirus known as SARS-CoV-2 [1], [2]. The disease was first identified in Wuhan, China, in late 2019, and has since rapidly spread across the globe [3], [4]. Common symptoms of COVID-19 include fever, dry cough, and fatigue, although some patients may also experience other symptoms such as shortness of breath, muscle aches, sore throat, and loss of taste and smell [5]. The disease spreads through respiratory droplets produced when an infected person coughs, sneezes, or talks, and can also be transmitted through contact with contaminated surfaces [6]. To prevent the spread of the virus, preventive measures such as regular hand washing, wearing masks, and maintaining physical distance from others are recommended by global health authorities.

One such advancement involves the use of Magnetic Resonance Imaging (MRI) to aid in the identification and evaluation of COVID-19-related complications, particularly in severe cases [7]. MRI technology enables healthcare professionals to assess the extent of lung damage and monitor the progression of the disease, providing crucial insights into the development of pneumonia and other respiratory complications associated with COVID-19 [8], [9]. The utilization of MRI has proven instrumental in facilitating early detection and monitoring of the disease, allowing for timely intervention and appropriate medical management to improve patient outcomes.

After carrying out the inspection phase, the utilization of Convolutional Neural Network (CNN) in the analysis of MRI images obtained from COVID-19 patients has significantly enhanced the accuracy and efficiency of disease classification. By leveraging this advanced deep learning technique, radiologists and healthcare professionals can precisely identify and categorize distinct patterns and anomalies present within the lung tissue, enabling a more precise differentiation between COVID-19-induced pneumonia and other respiratory ailments. The CNN model effectively extracts intricate features and intricate spatial relationships from the MRI scans, allowing for a robust classification process that aids in the early detection and comprehensive assessment of the disease progression, ultimately contributing to the development of tailored treatment strategies and improved patient care.

In this study, researcher employed Convolutional Neural Network (CNN) methodology to analyze the complex patterns and abnormalities identified in the magnetic resonance imaging (MRI) scans of patients afflicted with COVID-19. Through the utilization of CNN, the researchers were able to efficiently extract intricate features and spatial information from the MRI data, facilitating the accurate classification and characterization of specific COVID-19-related lung pathologies and complications. In the following subsection, this research will provide a detailed account of the implementation of the Convolutional Neural Network (CNN) method in the analysis of MRI images of COVID-19 patients. Furthermore, we will explicate the framework employed for monitoring disease progression and therapeutic response during the course of the study. Finally, this subsection will highlight the significant conclusions derived from this research, emphasizing the substantial contribution of the CNN methodology in enhancing the diagnostic accuracy and therapeutic management of COVID-19 patients.

2. RESEARCH METHOD

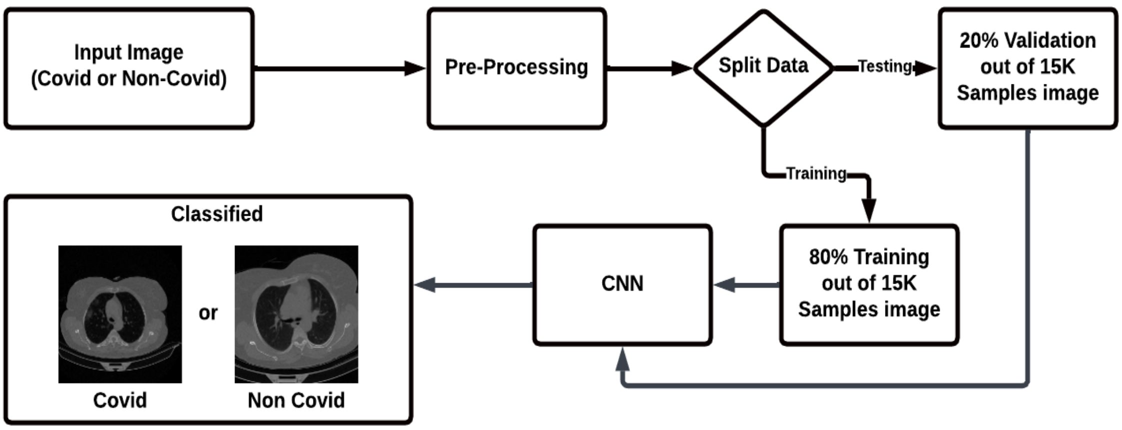


Figure 1. Research Methodology

The methodology of the study involved a systematic approach, starting with the acquisition of a diverse dataset consisting of images labeled as either "Covid" or "Non-Covid." The images were subjected to a pre-processing stage to ensure uniformity and optimize the quality of the data for subsequent analysis. Following this, the dataset was divided into training and validation sets, with 80% of the 15,000 sample images allocated for CNN training and 20% for validation purposes. The training phase of the CNN involved the utilization of the training dataset for the model to learn and recognize distinct patterns associated with Covid and Non-Covid cases. The testing phase was then conducted to assess the accuracy and performance of the trained CNN model in classifying new, unseen images into the respective Covid and Non-Covid categories.

2.1. MRI Image

Magnetic resonance imaging is a type of examination that uses a strong magnetic field and radio waves to produce detailed images of the inside of the body. Images from MRI results can help doctors diagnose various health problems. In an MRI test, the part of the body to be scanned is placed in a machine that has very strong magnetic strength. The images produced from an MRI are digital photos that can be stored on a computer and printed for further study.

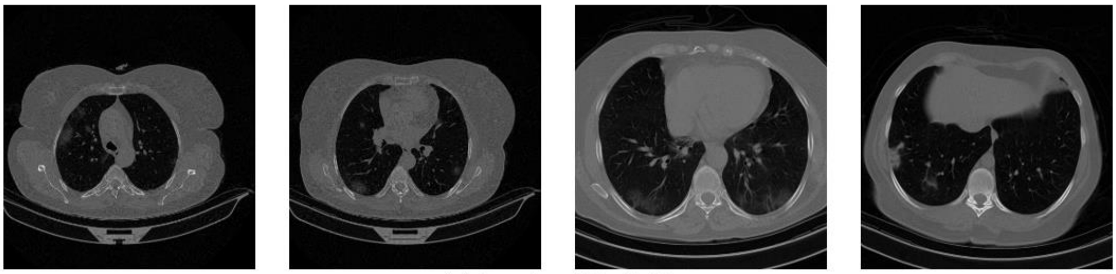
MRI is often performed and is related to examination of the brain, spinal cord, heart, blood vessels, bones, joints, soft tissue and other body organs. An MRI examination requires the help of a special dye that is injected through a blood vessel, to help increase the accuracy of the image as a result of the examination. Examination of body organs through an MRI procedure is often considered a safer method. Because, unlike X-rays or CT scans, MRI examinations do not emit radiation so they are quite safe to do even for pregnant women.

The MRI procedure can be carried out on a number of certain body organs, to detect abnormalities or health problems that may attack. There are various organs that are usually examined via MRI, including:

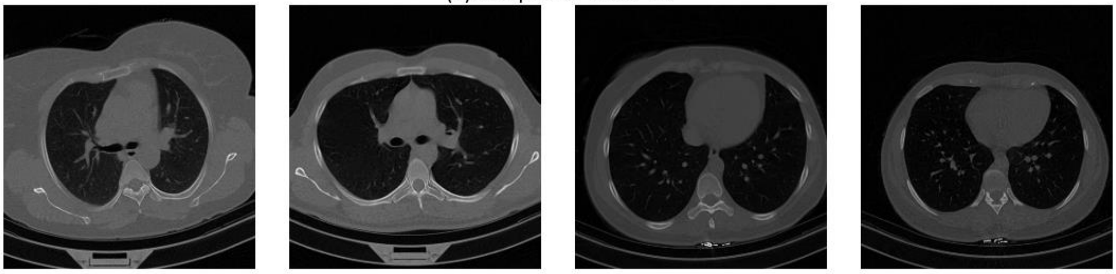
a. Brain and Spinal Cord.
   An MRI examination of the brain and spinal cord is carried out to detect several health problems that may occur. MRI can be done to detect head injuries, cancer, stroke, blood vessel damage to the brain, tumors, spinal cord injuries, abnormalities in the eyes or inner ear, and multiple sclerosis.
b. Heart and Blood Vessels.
   An MRI procedure can be performed to check the condition of the heart and blood vessels. Usually, this method is used to detect blood flow disorders or inflammation in the blood vessels. This method can also detect heart disease, heart damage after a heart attack, abnormalities in the structure of the aorta, such as aortic dissection or aneurysm, as well as abnormalities in the structure of the heart organ which include the size and function of the heart chambers, thickness and movement of the heart walls.
c. Bones and Joints.
   MRI can also be used to detect diseases of the bones and joints. For example, bone infections, bone cancer, and joint injuries. Apart from these organs, this examination can also be carried out on other parts of the body. MRI can be done to check for abnormalities in the breasts, uterus and ovaries, liver, bile ducts, spleen, kidneys, pancreas or prostate.

2.2. Datasets

The dataset utilized in this research was obtained from Kaggle, a prominent platform for open-access datasets. Comprising a comprehensive collection of images labeled as "Covid" and "Non-Covid," the dataset was meticulously curated to ensure diversity and representativeness of the various manifestations of Covid-19. Leveraging the abundance of data, the researchers meticulously partitioned the dataset into distinct subsets, with 80% of the 15,000 sample images earmarked for the training phase of the Convolutional Neural Network (CNN). The remaining 20% of the dataset was dedicated to the validation set, serving as a crucial component in the assessment of the CNN's efficacy in accurately classifying and distinguishing between Covid and Non-Covid images. Sample of datasets can be shown below:



(a) Samples of Covid-19



(b) Samples of Non Covid-19

Figure 2. Sample Datasets

2.3. Pre-Processing

In the pre-processing phase, the research team implemented a series of essential steps to ensure the standardization and optimization of the image data before feeding it into the Convolutional Neural Network (CNN) [10], [11]. This involved the normalization of the image data to enhance uniformity and reduce any potential variations in pixel intensity across the dataset. Additionally, the images underwent a resize operation, enabling uniform dimensions and resolution consistency, which proved pivotal in facilitating an efficient computational process during the subsequent training and validation stages. Pre-processing can be shown below:

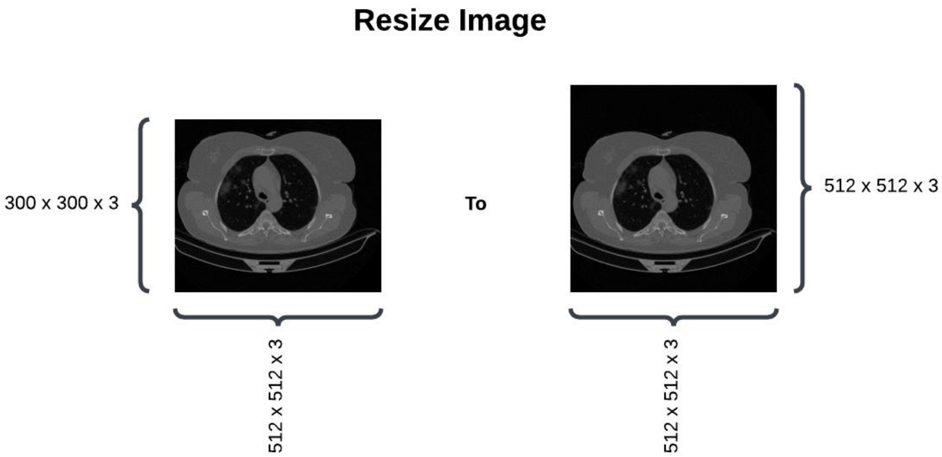


Figure 3. Pre-Processing

2.4. Convolutional Neural Networks (CNN)

Convolutional neural networks are distinguished from other neural networks by their superior performance on input images, speech, or audio signals [12], [13]. CNN has three main types of layers, namely:

1. Convolution layer
2. Pooling layer
3. Fully connected layer (FC-fully connected)

The convolution layer is the first layer of a convolutional network. Although a convolutional layer can be followed by additional convolutional layers or pooling layers, a fully connected layer is the last layer. At each layer, the complexity of the CNN increases, to identify larger parts of the image. Initial layers focus on simple features, such as color and edges. As the image data advances through the layers of the CNN, the layers begin to recognize elements or shapes of larger objects until they finally identify the object in question.

In the context of Covid-19 classification, the Convolutional Neural Network (CNN) played a pivotal role in enabling the accurate and efficient identification of intricate patterns and distinct features associated with Covid-19 infections [12], [13]. Leveraging the power of deep learning, the CNN algorithm systematically analyzed the pre-processed image data, extracting and learning intricate spatial hierarchies and patterns within the lung tissue. Through multiple layers of convolutions, pooling, and non-linear activations, the CNN model adeptly discerned subtle differentiators between Covid and non-Covid cases, thereby enhancing the diagnostic capabilities in identifying specific radiological manifestations unique to Covid-19 [14]. The CNN's ability to learn complex representations from the image data contributed to the precise classification of Covid-19 cases, ultimately fostering advancements in early detection and facilitating timely interventions for effective patient management and treatment. Based on CNN Layers can be shown below:

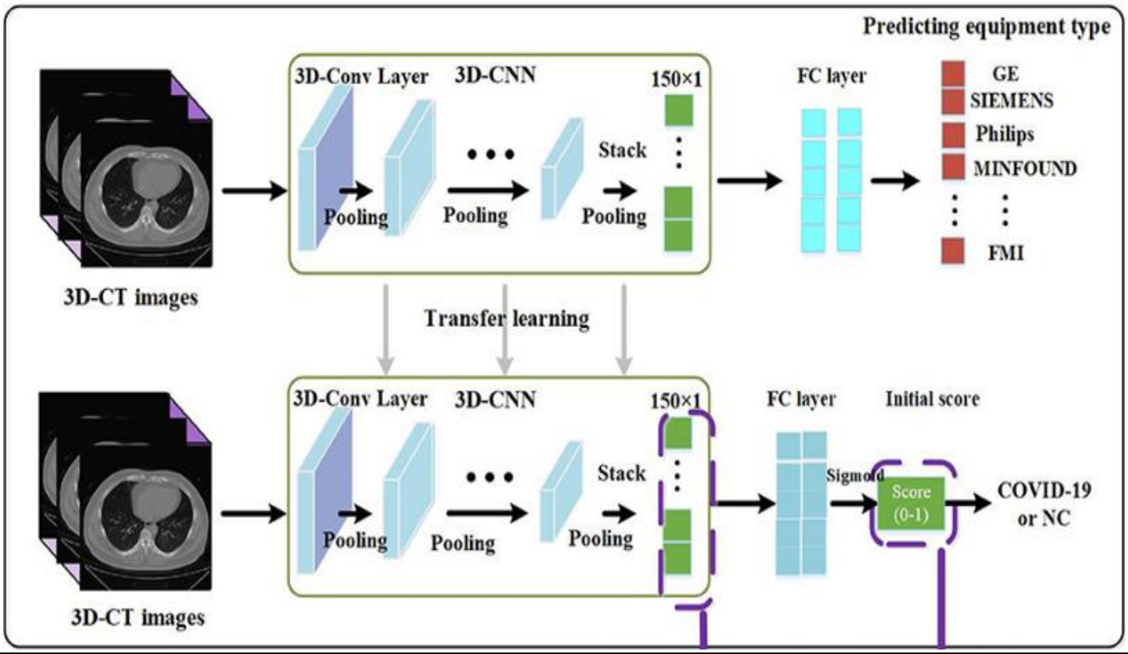


Figure 4. CNN Layers

2.5. Confusion Matrix Evaluation

In the evaluation of the Covid-19 classification, the research team employed a comprehensive Confusion Matrix analysis, a pivotal tool in assessing the performance and efficacy of the classification model. By systematically organizing the predicted classifications against the actual classes, the Confusion Matrix enabled the researchers to derive essential metrics such as accuracy, precision, recall, and F1 score, offering a holistic understanding of the model's ability to accurately discern between Covid and non-Covid cases.

Through the examination of true positives, true negatives, false positives, and false negatives, the Confusion Matrix provided crucial insights into the model's strengths and potential areas for improvement, enabling the researchers to fine-tune the CNN parameters and optimize the classification accuracy. The thorough analysis of the Confusion Matrix outcomes facilitated a comprehensive evaluation of the model's robustness and reliability in the classification of Covid-19 cases, ultimately contributing to the refinement of diagnostic tools and methodologies for improved healthcare management [15]. Based on Confusion matrix evaluation can be shwon in equation below:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

$$F1 - score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

Within the framework of the confusion matrix, True Positive (TP) signifies the count of correctly identified positive instances by the model, whereas False Positive (FP) refers to the number of negative instances mistakenly categorized as positive. False Negative (FN) denotes the instances of positive samples that were erroneously classified as negative, while True Negative (TN) represents the accurate identification of negative instances by the model.

3. RESULTS AND DISCUSSION

The discussion of the study's findings was centered around the comparison and analysis of the performance of the Convolutional Neural Network (CNN) using three different optimization parameters, namely Adam, RMSP, and SGD. The evaluation encompassed the examination of various key performance metrics, including accuracy, precision, recall, and F1 score, derived from the model's performance under each optimization parameter. The comprehensive assessment of the CNN's performance under these distinct optimization techniques shed light on the impact of each parameter on the model's ability to accurately classify Covid and non-Covid cases.

This analysis, presented in Table 1, provided valuable insights into the efficacy of different optimization algorithms in enhancing the CNN's discriminative capabilities and optimizing its overall performance, facilitating informed decision-making for future refinement and optimization of the classification model. The utilization of the three different optimization methods, namely Adam, SGD, and RMSP, was instrumental in optimizing the training process of the Convolutional Neural Network (CNN), as illustrated in Table 1. The study incorporated various configurations for each optimization technique, including 20 MaxEpoch and 30 Validation Frequency, with a consistent initial learning rate of 0.0001.

Table 1. Training Option

1st Training Option	2nd Training Option	3rd Training Option
Adam Optimalization	SGD Optimalization	RMSP Optimalization
20 MaxEpoch	20 MaxEpoch	20 MaxEpoch
30 Validation Frequency	30 Validation Frequency	30 Validation Frequency
0.0001 Initial Rate	0.0001 Initial Rate	0.0001 Initial Rate

The comprehensive examination of the model's performance under these distinct optimization approaches, as depicted in the graphical representation in Figure 5, provided a detailed comparative analysis of the CNN's training outcomes, elucidating the impact of each optimization method on the model's convergence rate, training accuracy, and overall stability. The insights derived from Figure 5 served as a valuable reference for discerning the most effective optimization strategy for enhancing the CNN's learning dynamics and improving its classification precision, thus contributing to the establishment of an optimized and efficient training framework for future CNN applications.

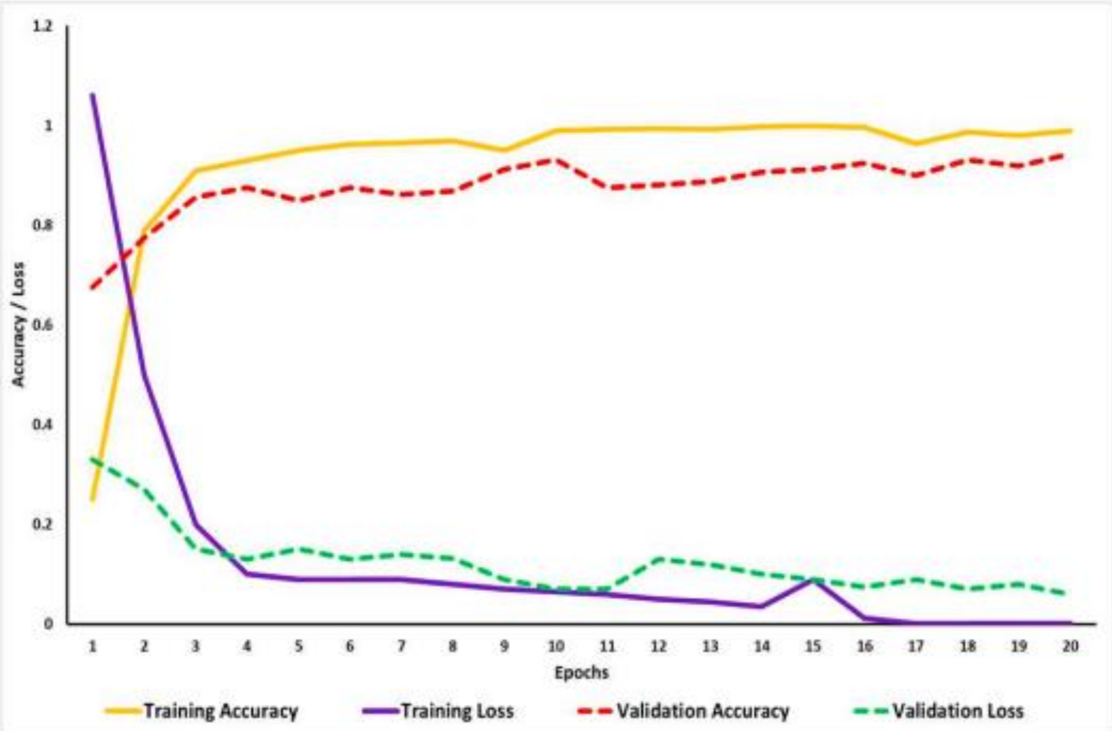


Figure 5. Training Graph based on Table 1

The results obtained from the analysis of the graphical representations in Figure 5 were instrumental in informing the comprehensive Confusion Matrix evaluation, as presented in Table 2. The Confusion Matrix provided an in-depth assessment of the classification model's performance under each optimization method, highlighting the variations in Accuracy, Precision, Recall, and F1-Score. Through the systematic analysis of these metrics, the study was able to ascertain the efficacy of each optimization approach in enhancing the CNN's precision and accuracy in differentiating between Covid and non-Covid cases.

Table 2. Confusion Matrix Evaluation

Optimalization	Accuracy	Precision	Recall	F1-Score
RMS Model	98%	100%	100%	100%
SGD Model	97%	99%	99%	99%
Adam Model	98%	100%	100%	100%

The RMS Model demonstrated exceptional accuracy of 98% and perfect precision, recall, and F1-Score of 100%, underscoring its efficacy in accurately discerning Covid and non-Covid cases. Similarly, the Adam Model showcased comparable results with an impressive 98% accuracy and flawless precision, recall, and F1-Score of 100%, reaffirming the effectiveness of the Adam optimization approach in achieving superior classification outcomes. After training phase, a systematic testing phase was conducted, as depicted in Figure 6. This testing phase enabled the evaluation of the accuracy and performance of the trained Convolutional Neural Network (CNN) model on the Covid-19 and non-Covid-19 datasets, facilitating a more precise and objective assessment of the classification accuracy before drawing final conclusions.

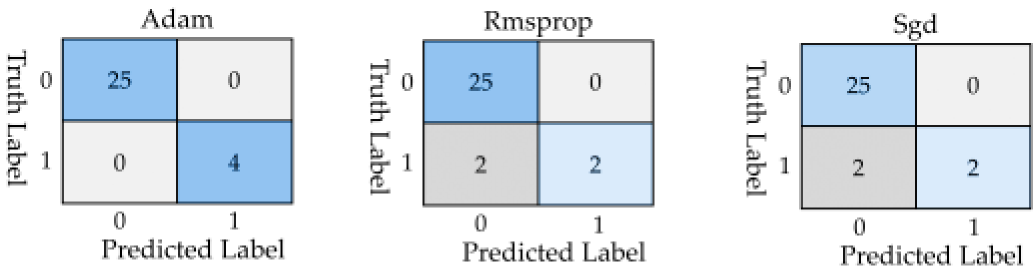


Figure 6. Testing Phase in 29 Samples

4. CONCLUSION

Based on the findings presented in Table 2, the evaluation of the classification models under different optimization methods yielded promising results, with all three models demonstrating high accuracy in distinguishing between Covid and non-Covid cases. The RMS Model exhibited a remarkable 98% accuracy, with perfect precision, recall, and F1-Score of 100%, highlighting its robust performance in accurately classifying both positive and negative instances. Similarly, the SGD Model demonstrated a commendable 97% accuracy, accompanied by a 99% precision, recall, and F1-Score, underscoring its strong discriminative capabilities in the classification of Covid-19 cases. Moreover, the Adam Model also attained an impressive 98% accuracy and a flawless precision, recall, and F1-Score of 100%, further reinforcing the efficacy of the Adam optimization method in enhancing the CNN's classification accuracy.

For future research endeavors, the incorporation of transfer learning methodologies, such as ResNet, LeNet, MobileNet, and similar architectures, holds significant promise in augmenting the existing framework for Covid-19 classification. Leveraging the pre-trained models and deep learning architectures, the integration of transfer learning techniques would facilitate the extraction of complex features and spatial representations from the image data, potentially enhancing the CNN's proficiency in discerning intricate patterns associated with Covid-19 pathology. Furthermore, the utilization of transfer learning models would expedite the training process, reduce the demand for extensive datasets, and promote the development of robust and scalable diagnostic tools for Covid-19 identification.

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