

The Development of An Accurate MobileNetV2 Computer Vision Algorithm for the Diagnosis of SARS-COV-2

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Innovate AI

DOI: 10.46609/IJSSER.2024.v09i11.041 URL: <https://doi.org/10.46609/IJSSER.2024.v09i11.041>

Received: 17 October 2024 / Accepted: 20 November 2024 / Published: 5 December 2024

ABSTRACT

As of August 2024, the World Health Organization reported 238,416 cases of the Coronavirus, also commonly referred to as COVID-19 (WHO, 24). There has been a reported total accumulation of 776,007,137 cases since the pandemic began in March of 2020. This virus spread all around the world killing over 7 million people while deeply harming those who tested positive. (Furthermore, COVID-19 caused significant economic downfall due to unemployment rates jumping to 5% and the major increases in global inflation. Proper diagnosis of COVID-19 is crucial towards helping society get their required medical assistance. Current traditional methods such as RT-PCR and antigen tests remain widely used, but come with their own limitations. For example, the supply of PCR kits is not sufficient to satisfy the need for rapid testing. Antigen tests have their own shortcomings, and require time to develop results. In order to fix the issue of delays and supply kit shortages, we implemented a computer vision model utilizing MobileNetV2 that inputs a patient's chest x-ray scan and outputs the covid result. While the model use depends on having an X-ray on hand, it enables rapid diagnosis for the high risk population, which may already have the necessary prerequisites. A model proved to be the most effective approach, as it required far fewer resources without sacrificing diagnosis quality. Our model successfully utilized dependencies and convolutional neural networks to output the result of a COVID chest x-ray scan after intense training and testing. Our product eliminated the need for ineffective methods of diagnosis and proved to be far more accurate.

Keywords: MobileNetV2, Machine Learning, AI, Covid, Diagnosis, Medicine

1. Introduction

COVID-19, otherwise known as Coronavirus, is a virus belonging to the Coronaviridae Family. The global pandemic virus originated in Wuhan, China (NFID, 24). SARS-CoV-2, the virus that causes COVID-19, starts its track by infecting the cells along the airways. It enters the cells by

attaching itself to a specific cell receptor, ACE-2, found in specified organs. COVID-19 primarily attacks the respiratory system but is known to attack other complex systems, such as the heart and brain. The virus uses ACE-2 as a doorway into the cells, where it then starts to take control of the cell's ability to replicate itself. Using the cell's reproductive ability, it replicates the virus RNA to infect more cells (NIH, 22).

The COVID-19 Pandemic has had significant impacts on livelihoods, economic stability, and health worldwide. The long-term effects of COVID-19 include persistent symptoms of fatigue, foggy memory, dizziness, issues with sleep, shortness of breath, cough, headaches, irregular heartbeat, and digestion problems. If left untreated, these symptoms, paired with older patients with underlying heart or other problems can lead to heart disease, strokes, blood clots, Postural orthostatic tachycardia syndrome, also known as POTS, Mast cell activation syndrome, or MCAS, and Fibromyalgia (Mayo Clinic, 24). In the past 28 days from August 11, 2024, around 3,742 people died. COVID-19 has led to significant social and economic disruption. Unemployment rates jumped to 4.9 percent globally as of October 2021, with 4.2 million fewer jobs than there were in February 2020 (Tracking the COVID-19 Economy's Effects on Food, Housing, and Employment Hardships, 22).

COVID-19 is diagnosed through molecular tests and antigen tests. The SARS-CoV-2 detection methods include antigen or antibody testing and the nucleic acid amplification test NAATS. NAATs specifically identify the RNA sequences that consist of the genetic material of COVID-19 (CDC, 21). The methods NAATs use to amplify nucleic acids include NEAR, TMA, LAMP, Crispr, HDA, and RT-PCR (CDC, 23) Molecular detection by RT-PCR is the gold standard for molecular detection and is the most widely used method for SARS-CoV-2 detection (NIH, 22). It functions through reverse transcription of SARS-CoV-2 RNA into cDNA and after, measuring viral load by cycle threshold. Antigen tests are immunoassays that detect viral proteins called antigens. Positive antigen tests indicate infection. The aforementioned tests are used as diagnosis methods for current infection of Sars-Cov-2, but antibody tests are utilized to test for the presence of antibodies from previous infection.

Antibody tests identify specific antibodies that target different components of the virus, such as the nucleocapsid or spike protein. The presence of anti-nucleocapsid antibodies suggests a SARS-CoV-2 infection, whereas anti-spike protein antibodies may result from either COVID-19 vaccination or a SARS-CoV-2 infection. (CDC, 24) This is important when deciding whether to test for antibodies from a previous infection or from vaccination.

Although these diagnosis methods are effective and are considered helpful, their shortcomings such as costly equipment, necessity for trained personnel, and false positive/false negative results cause the diagnosis methods to be inefficient. For RT-PCR diagnosis, the supply of PCR kits

cannot meet the excess demand and the efficiency depends heavily on the presence of SARS-COV-2 in the samples. Furthermore, these methods can be influenced by various factors, including insufficient sample volume, improper sample collection, inaccurate techniques, incorrect timing for sample collection, and contamination. This makes the diagnosis methods overall inefficient and expensive. As a result, our computer vision model is better than the current diagnosis methods because it utilizes few resources, solely a computer and chest x-rays, but maintains high accuracy.

Our solution utilizes Python's programming language, open-source Keras software library, Numpy library, and tensor flow for model creation. The specific algorithm we employed was MobileNetV2; the entire program was written within the Google Colaboratory data science notebook, where we leveraged an external GPU.

2. Procedures

We used the algorithm MobileNetV2 due to its allows for a high accuracy and speed whilst using minimal computational resources. MobileNetV2, having been developed by AI teams at Google, was favored for its status as a model capable of being deployed on the edge (edge computing is the most likely route of expansion for this project). The main dependencies we used were tensorflow, keras, and numpy. Tensorflow and Keras served as the ML framework for our model. We used MobileNetV2 as our base architecture, however we added 5 new layers and only trained the last 5 layers on our new data. We used mobile net via transfer learning, and added 5 layers (a combination of GlobalAveragePooling2D and Dense) with the RELU activation function being used for intermediary layers and the sigmoid activation function for our final layer. The RELU activation function was used due to its ability to solve issues with gradient descent for the loss function. We used sigmoid because it outputs a value between 0 and 1 and is used for binary classification. The binary cross entropy loss function was utilized to evaluate the accuracy and loss of the model's predictions. Finally, the adam optimizer was applied to optimize the loss function and gradient descent.

This model was trained upon a dataset obtained from Kaggle. 181 images were used for training, and 46 images were used to test the model. This is a comparatively smaller dataset when referenced with traditional computer vision projects.

2.1. Image Preprocessing

For preprocessing the images to train and test our model, we rescaled and normalized the rgb values to 1/255 to make the color features on the same scale of 0-1. Each of the images were resized into 200 x 200 for the model to interpret.

2.2. Training

We utilized binary cross entropy as the loss function to evaluate the accuracy of the predictions, this choice was made as binary is well suited for yes or no classifications. We employed the Adam optimizer with a learning rate of 0.0001 to traverse and optimize the gradient descent and decrease training time. A batch size of 15 was used to assure that the model does not overload and we used 10 epochs to thoroughly train the model.

2.3. Evaluating

The repurposed MobileNetV2 model was trained for 10 epochs. The system had a learning rate of 0.0001, an accuracy of 1.000, a loss of 0.0090, a validation accuracy of 1.000 and a validation loss of 0.0086.

2.4. Metrics

The Keras library used in the model allowed for a variable titled "loss" to be included in the end of each epoch output line. The loss was a value ranging from 0-1 determined by the binary cross entropy. The loss value reached 0.0090 with an accuracy of 1.000, while the validation loss value achieved a minimum of 0.0086 and a validation accuracy of 1.000.

Conclusion

As a result of our computer vision model that utilizes the MobileNetV2 CNN, our model was able to appropriately identify whether a chest x-ray exhibited COVID or not, displaying a final accuracy of 1.000 and a loss of 0.009. Our computer vision model allows for a high efficiency and a cost effective diagnosis of COVID - 19. Compared to current options such as RT-PCR diagnosis and antigen diagnosis, our model utilizes far fewer resources and is capable of meeting the high demands of COVID diagnosis. This method of diagnosis is important as it allows for easier accessibility to the majority of the population and advises those to seek immediate medical assistance. In the future, we plan on making our machine model easily accessible through an application and website where the public can take advantage of our model, eliminating the need for RT-PCR diagnosis as they are inefficient and are in low supply. Of course, there still remains a need for high quality x-ray samples in order to perform the diagnosis with the model. Nevertheless, populations that are at high risk may already have the necessary inputs at hand, proving the efficacy of this solution.

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