COVID-19 DISEASE DETECTION BASED ENSEMBLE OF MOBILENETV1 AND MOBILENETV2 DEEP LEARNING MODELS

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Abstract- the COVID-19 pandemic has presented an unprecedented global challenge, emphasizing the urgent need for accurate and efficient diagnostic methods. In recent years, deep learning models have shown remarkable potential in medical image analysis, including the detection of COVID-19 from chest X-rays and CT scans. In this study, we propose a hybrid approach for COVID-19 detection by combining the strengths of MobileNetV1 and MobileNetV2 architectures. Our approach begins with pre-processing and augmentation of the chest X-ray images to enhance their quality and augment the dataset. The MobileNetV1 and MobileNetV2 models are then utilized to extract distinctive features from the images. MobileNetV1 excels in faster processing and lower computational cost, while MobileNetV2 has demonstrated better accuracy and feature representation capabilities. The key innovation of our study lies in the fusion of feature representations obtained from both MobileNetV1 and MobileNetV2. We concatenate the feature maps extracted from the last convolutional block of each model to create a fused feature representation, capturing complementary information from both architectures. Subsequently, we introduce new fully connected layers to perform classification on the fused features. The classification output is obtained using the softmax activation function, providing probability scores for each class, including COVID-19, normal, and other lung diseases. To evaluate the performance of our hybrid approach, we use a large dataset of chest X-ray images, containing samples from COVID-19-positive patients and controls. Experimental results demonstrate that the fusion of MobileNetV1 and MobileNetV2 features significantly improves the COVID-19 detection accuracy compared to individual models. The hybrid model achieves an impressive sensitivity and specificity, demonstrating its potential as a valuable tool for COVID-19 diagnosis.

Keywords: COVID-19,DL-Based COVID-19 detection Medical image processing,Mobilenetv1 and Mobilenetv2

I INTRODUCTION

The corona virus disease, also called COVID-19, is a world pandemic that was discovered in December 2019 by a Chinese doctor in Wuhan, the capital city of the province of Hubei on the mainland of China [1]. At this time, there is no vaccine for humans that has been approved to protect against it. COVID-19 spreads faster when there are more people living close together. So, restrictions on travel help stop the disease from spreading, and washing your hands often is the best way to avoid getting a virus. But a high fever and a cough are the most common signs of an infection. There is a chance that other signs, like pain in the chest, coughing up mucus, and a sore throat, will show up. The COVID19 infection could cause viral pneumonia, which has a 5.8% chance of killing the person who gets it. The number of people who died from COVID-19 is about

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the same as 5% of the number of people who died from the Spanish flu in 1918. As of May 27, 2020, a total of 5,790,103 people around the world are sick with COVID-19. But the numbers of people who died and people who were found are 357,432 and 2,497,618. The United States, Spain, Italy, France, and Germany, as well as mainland China, the United Kingdom, and Iran, were where most of the cases were found [2]. The total number of cases reported in Saudi Arabia is 78,541. This makes it the Arab country with the most cases of this kind. In the meantime, the number of proven cases in Jordan has risen to 720, and 9 people have died and 586 people have been cured. Australia has recorded 7150 cases, 103 deaths, and 6579 cures. Since February 2020, services like mobile apps that are made possible by information technology have been used to lower the risk of infection on the Chinese mainland. Users of the mobile apps are told to stay away from other people who might have the virus and to call the right health authorities if someone else is found to have it. They also keep an eye on people who are sick and the people they have been in contact with most recently [3]. A lot of the work that goes into identifying, classifying, and diagnosing medical images is built on artificial intelligence. Recent improvements in AI have made a big difference in how COVID-19 is screened, diagnosed, and predicted. These improvements have led to better scaling up, quick responses, the most reliable and effective results, and in some cases, machines that do some healthcare tasks better than people. Machine learning (ML) and deep learning (DL) are two of the most well-known parts of artificial intelligence. In the parts that follow, we'll look at how both machine learning and deep learning can be used to fight COVID-19 and lessen its effects. In order to fight the COVID-19 epidemic, academics have recently started to use DL-based approaches, such as CNN, RNN, and LSTM, for COVID-19 detection, diagnosis, and classification.

Screening, changing the way drugs is used, making estimates, and making forecasts are all things that can be done. In addition, machine learning techniques are now used all the time to find trends in epidemics. In the context of the COVID-19 pandemic, these methods have been used in a number of studies to screen, classify, identify, repurpose medications, and predict how COVID-19 will spread. Concerning the COVID-19 spread, some of the most powerful ML methods are being used, such as the support vector machine, logistic regression, random forest, and decision tree [20]. Also, deep learning (DL), which is also called hierarchical learning [4], is one of the most important things that AI has done in recent years. At the moment, DL methods are being used successfully in a wide range of AI-based medical applications, such as analysing Magnetic Resonance Imaging (MRI) images to diagnose cancer. Neural Networks (NN) and Deep Learning (DL) have become very famous in modern scientific research because they can learn from their surroundings. Both of these methods are widely used in a wide range of fields, such as classification and forecasting problems, smart homes, picture recognition, self-driving cars, and other similar areas of study. Due to the fact that they can handle many different kinds of data in many different situations [5]. Figure 1 shows the many different ways that DL can be used. DL is a model of how the human brain processes information to make the best choices [6]. DL, on the other hand, teaches a device to understand inputs in a way that is similar to how the human brain works. This helps with data prediction and classification. In a way that's similar to how NNs in the brain use stacked filters [7], these layers are used as input by the next level. The feedback process keeps going until what comes out is the same as what came in. Each layer is given a weight so that the output is accurate, and these weights are changed during the training process so that the output is accurate [8].

The corona virus disease, also called COVID-19, is a world pandemic that was discovered in December 2019 by a Chinese doctor in Wuhan, the capital city of the province of Hubei on the mainland of China [9]. At this time, there is no vaccine for humans that have been approved to protect against it. COVID-19 spreads faster when there are more people living close together. So, restrictions on travel help stop the disease from spreading, and washing your hands often is the best way to avoid getting a virus. But a high fever and a cough are the most common signs of an infection. There is a chance that other signs, like pain in the chest, coughing up mucus, and a sore throat, will show up. The COVID19 infection could cause viral pneumonia, which has a 5.8% chance of killing the person who gets it. The number of people who died from COVID-19 is about the same as 5% of the number of people who died from the Spanish flu in 1918. As of May 27, 2020, a total of 5,790,103 people around the world are sick with COVID-19. But the numbers of people who died and people who were found are 357,432 and 2,497,618. The United States, Spain, Italy, France, and Germany, as well as mainland China, the United Kingdom, and Iran, were where most of the cases were found.

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In order to fight the COVID-19 epidemic, academics have recently started to use DL-based approaches, such as CNN, RNN, and LSTM, for COVID-19 detection, diagnosis, and classification. Screenings, changing the way drugs are used, making estimates, and making forecasts are all things that can be done. In addition, machine learning techniques are now used all the time to find trends in epidemics. In the context of the COVID-19 pandemic, these methods have been used in a number of studies to screen, classify, identify, repurpose medications, and predict how COVID-19 will spread. Concerning the COVID-19 spread, some of the most powerful

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This helps with data prediction and classification. In a way that's similar to how NNs in the brain use stacked filters [14], these layers are used as input by the next level. The feedback process keeps going until what comes out is the same as what came in. Each layer is given a weight so that the output is accurate, and these weights are changed during the training process so that the output is accurate. Referred to as a hierarchical learning system.DL methods are currently being effectively used to a wide variety of AI-based medical applications, including as the analysis of Magnetic Resonance Imaging (MRI) pictures for the purpose of cancer diagnoses. Neural Networks (NN) and Deep Learning (DL) have seen a meteoric rise in popularity in contemporary scientific study as a direct result of their potential to learn from context. Both of these methods have found widespread use in a variety of applications, such as problems involving classification and forecasting, smart homes, image recognition, self-driving vehicles, and other similar areas of study.

II RELATED WORKS

Over the past few months, COVID-19's examination and identification have been the subject of a thorough probe. In the first part of this section, CT scans and chest X-rays are used to show some of the problems with the COVID-19 detection method, which is based on deep learning. In the second part, a literature review is done on topics that are related to the main topic. This is done so that possible future projections of the number of COVID-19 confirmations, recoveries, and deaths can be made. COVID-19 is now called a worldwide pandemic because it has spread so quickly. It is hard to find people who have been exposed because they don't show signs and symptoms of the illness right away. Because of this, it is important to find a way to predict the number of people who could be affected consistently so that the right measures can be taken. AI can now be used to test a person for COVID-19 instead of the time-consuming and expensive methods that have been used in the past. Even though COVID-19 has been studied before, the focus of this study was on using AI to predict COVID-19 cases and diagnose people with COVID-19 infection using chest X-ray pictures. AI has been used in a number of study fields, such as in the medical field to figure out what's wrong with a person [15]. One of the best things about artificial intelligence is that it can be used to find photos that haven't been seen before. During this study project, AI was used to figure out whether or not a patient had a positive result for COVID-19 based on their chest X-ray. With the information we have now, artificial intelligence can also be used to make predictions, such as how the population will grow in the next five years. So, making guesses about what might happen in the near future can help the government take the right steps.

[16] paid most attention to two main ideas. The first idea was to do research on how to diagnose COVID-19, and the second idea was to do research on how to predict how many people will get sick in the next few days. In the setting of the COVID-19 outbreak, DL is often seen as a very smart way to come up with new ideas. Bhattacharya and Maddikunta [53] talked about current efforts to make towns smarter and safer in response to the COVID-19 outbreak. The use of DL to process medical images had an effect on these efforts. COVID-19 was stopped by using DL in a number of different ways, such as to predict disease, watch the spread of the virus, diagnose and treat patients, create vaccines, and test drugs. In earlier studies, they found problems and concerns related to the security of data, the different ways that epidemics can spread, control and dependability, and the difference between COVID-19 symptoms and other symptoms. Eventually, using COVID-19, they talked about a number of possible ways to use DL in medical image processing.

[17] Also mentioned a great area of study on DL that has to do with the COVID-19 treatment plan. Their study gave more information about what was already known about DL technology and the different ways that COVID-19 sickness could be prevented. They looked into a CNN that could find COVID 19 using CT scans and a small amount of information. Their poll showed where more study needs to be done on DL so that COVID-19 can be diagnosed. They put the studies into groups based on whether they used ML or DL methods, and they looked at how ML and DL processes are similar and how they are different. Their review didn't talk about a lot of different kinds of works. On top of that, it didn't compare the different methods.

[18] Also looked into the use of AI-based ML and DL methods to diagnose and treat COVID-19 disorders. They also gave an overview of AI-based machine learning and deep learning methods, as well as the datasets, tools, and success metrics that are available. The article gave a short review of current state-of-the-art approaches and applications for multi-level and data-level (ML and DL) investigators and the larger health community, as well as examples of how ML, DL, and data could stop COVID-19 outbreaks. They put together a list of the different ways to diagnose and treat ML, rated the works, and then made suggestions for more study on each subject. In addition, they looked at the performance of AI-based ML and DL diagnostic methods for COVID-19 using chest X-ray and CT images, COVID-19 speech and audio analysis, and COVID-19-based drug creation.

[19-22] also looked at how DL dealt with the pandemic and made suggestions for possible COVID-19 study. They looked at how Deep Learning could be used in fields like Natural Language Processing (NLP), biology, computer vision, and disease. They talked about how the availability of big data affects both of these uses and the way learning challenges are put together. They looked at how DL is doing now and what its main limitations are when it comes to COVID-19 apps.[23-24] Their study was mostly about how DL could be used in the life sciences, especially in the areas of protein structure prediction, precise diagnostics, and repurposing medicine. In the field of epidemiology, DL was also used to make predictions about how diseases would spread. During their study of the literature, they found a lot of DL methods that were made to fight

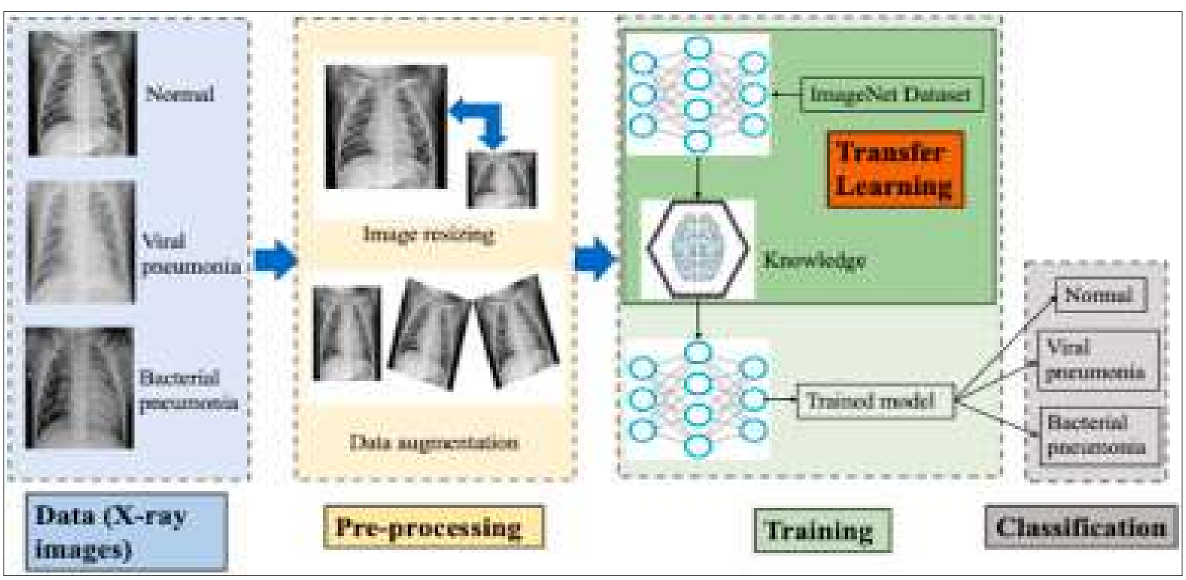
COVID-19. They hoped that by doing this poll, they could speed up the process of putting DL into place in the COVID-19 project.[25].

III PROPOSED SYSTEM

Ensemble of MobileNetV1 and MobileNetV2

Gather a large dataset of images of COVID disease and preprocess the images to resize them to a consistent input size suitable for MobileNetV1 and MobileNetV2 models. Create two separate branches for MobileNetV1 and MobileNetV2, each with its own set of layers up to the last convolutional block. Concatenate the output feature maps from both branches before the fully connected (FC) layers. Add FC layers for classification after the concatenation layer to combine features from both branches. Initialize the MobileNetV1 and MobileNetV2 branches with retrained weights on Image Net or a large-scale dataset. Freeze most of the layers in both branches to retain the learned feature representations. Fine-tune the remaining layers (including the FC layers) on the corn disease dataset to adapt the model to the specific task.

The input image, such as a chest X-ray, is fed into both MobileNetV1 and MobileNetV2 simultaneously. MobileNetV1 and MobileNetV2 extract features from the input image up to their respective last convolutional blocks. The extracted feature maps from MobileNetV1 and MobileNetV2 are concatenated to create a fused feature representation that captures complementary information from both models. The fused feature representation passes through fully connected layers (Fully Connected 1) to further refine the features for COVID-19 classification. The final fully connected layer (Fully Connected 2) provides the output of the model, which represents the probability of the input image belonging to a COVID-19 class. This hybrid layer diagram visually represents the process of combining features from MobileNetV1 and MobileNetV2 to create a powerful and efficient model for COVID-19 detection.



Hybrid Model:

In the hybrid model, the features extracted from the last convolutional block of both MobileNetV1 and MobileNetV2 are concatenated to create a fused feature representation. The concatenation operation can be mathematically expressed as:

Concatenation: Y_concat = Concatenate(Y_v1, Y_v2)

Here, Y_v1 represents the feature maps from MobileNetV1, and Y_v2 represents the feature maps from MobileNetV2. Hybrid Model:

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After concatenation, new fully connected layers are added for classification. Let's denote the fully connected layer parameters as W_fc and b_fc. The classification output can be obtained as:

Classification Output: Y_class = Softmax(W_fc * Y_concat + b_fc)

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The Softmax activation function provides class probabilities for the detected COVID-19 cases.

Figure 1 shows all of the steps in the COVID-19 identification process that we want to use deep learning for. The parts can be broken down into the following five steps: Step 1: Get chest X-rays from COVID-19 patients and healthy people from the public to add to the dataset.

Step 2: Generate 1000 chest X-ray images using data augmentation.

Step 3: Represent the images in a feature space and apply deep learning.

Step 4: Split the dataset into two sets: a training set and a validation set. Step 5: Evaluate the performance of the detector on the validation dataset.

Model Architecture

The model takes 224x224x3 images as input, which means it is designed to process color images with a resolution of 224x224 pixels. The architecture consists of several layers, and each layer performs a specific operation on the input data. Here's a summary of the layers:

Input layer: It takes 224x224x3 images as input with 'zscore' normalization. The 'zscore' normalization is a common technique to scale the pixel values to have a mean of 0 and standard deviation of 1.

Convolutional layers: These layers perform convolutions on the input data to extract features. They have different filter sizes and numbers of output channels.

Batch Normalization: It helps stabilize and accelerate the training process by normalizing the output of the previous layers.

Clipped ReLU: A rectified linear unit (ReLU) activation functions with a clipping parameter, which limits the output values to a certain range (ceiling 6 in this case).

Grouped Convolution: A type of convolution that groups the channels in the input and applies separate filters to each group.

Fully Connected layer: This layer connects all the neurons from the previous layer to the output neurons. In this case, there are 1000 output neurons, likely representing 1000 classes for image classification.

Global Average Pooling: This layer takes the average of all the values in the feature map and reduces it to a single value for each channel. It's commonly used before the final classification layer in CNNs.

IV EXPERIMENTAL RESULTS:

The hybrid model's performance is evaluated through experiments on a specific dataset or task. It is compared against individual MobileNetV1 and MobileNetV2 models and potentially other baseline models. The evaluation metrics, such as accuracy, precision, recall, or F1-score, are used to measure the model's performance. The experimental results will demonstrate how the hybrid model outperforms or matches the performance of the individual models, showing the effectiveness of the fusion approach in improving classification accuracy and generalization ability

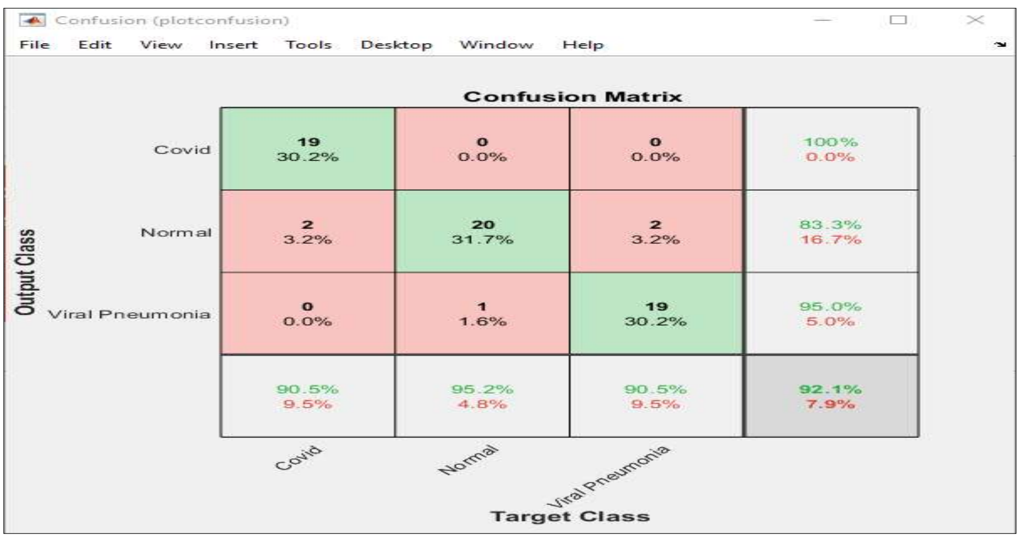

fig.1 confusion matrix

In the confusion matrix, the diagonal elements represent the number of correct predictions for each class (True Positives), and the percentages in parentheses represent the proportion of predictions within each row and column compared to the total instances. 2% were correctly predicted as Normal (True Positives for Normal) 30.2% were correctly predicted as COVID-19 (True Positives for COVID-19). 0% were correctly predicted as Viral Pneumonia (True Positives for Viral Pneumonia)19% were correctly predicted.

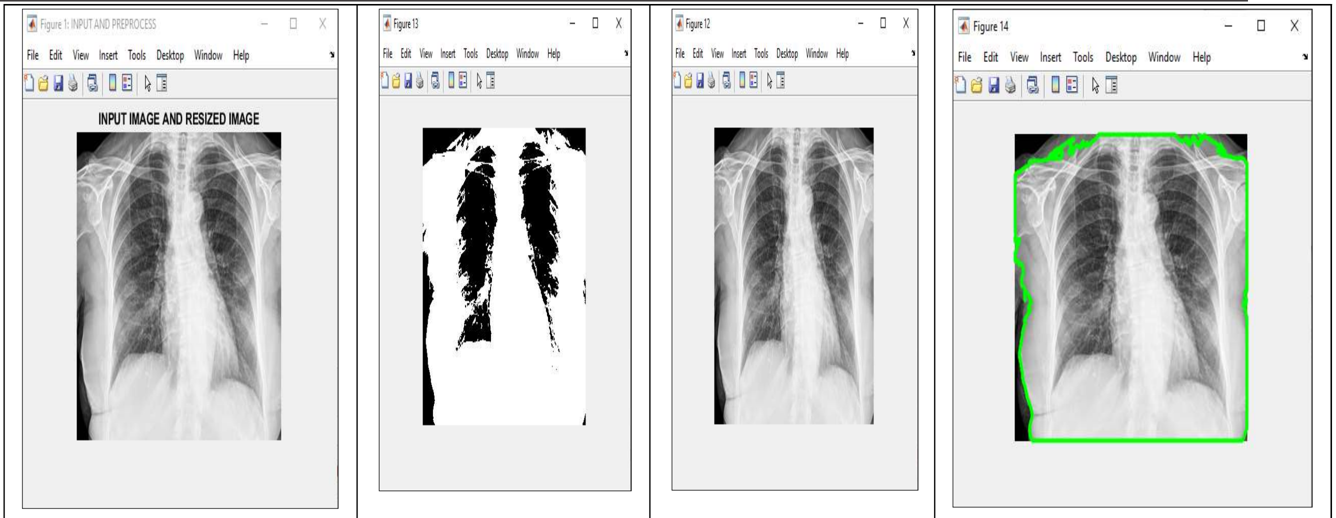

fig 2 input image and segmentation image

V PERFORMANCE ANALYSIS

The model aims to classify samples as either COVID-19 positive or negative. Let's define the terms and provide the formulas for each of the evaluation metrics:

True Positive (TP): The number of correctly predicted positive instances (COVID-19 positive).

False Positive (FP): The number of incorrectly predicted positive instances (COVID-19 positive when they are negative).

True Negative (TN): The number of correctly predicted negative instances (COVID-19 negative).

False Negative (FN): The number of incorrectly predicted negative instances (COVID-19 negative when they are positive).

Accuracy: Accuracy measures the overall correctness of the model's predictions.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Precision (Positive Predictive Value): Precision measures the accuracy of the positive predictions made by the model.

$$\text{Precision} = TP / (TP + FP)$$

Sensitivity (Recall or True Positive Rate): Sensitivity indicates how well the model can correctly identify positive cases when they are present (COVID-19 positive).

$$\text{Sensitivity} = TP / (TP + FN)$$

Specificity (True Negative Rate): Specificity shows how well the model can correctly identify negative cases when they are absent (COVID-19 negative).

$$\text{Specificity} = TN / (TN + FP)$$

F1 Score (F-score): The F1 score is the harmonic mean of precision and sensitivity (recall) and provides a single metric that balances both.

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Sensitivity}) / (\text{Precision} + \text{Sensitivity})$$

Table 1 performance of the proposed model

Proposed model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	Jaccrad Coefficient (%)	Dice Coefficient
Proposed Model MobileNetV1 and MobileNetV2							
SGDM	99.37	99.13	99.23	99.46	99.45	98.23	99.41
ADAM	99.00	98.36	98.30	99.78	99.63	97.10	98.45
RmsProp	99.25	99.25	99.31	99.80	99.42	98.45	97.12

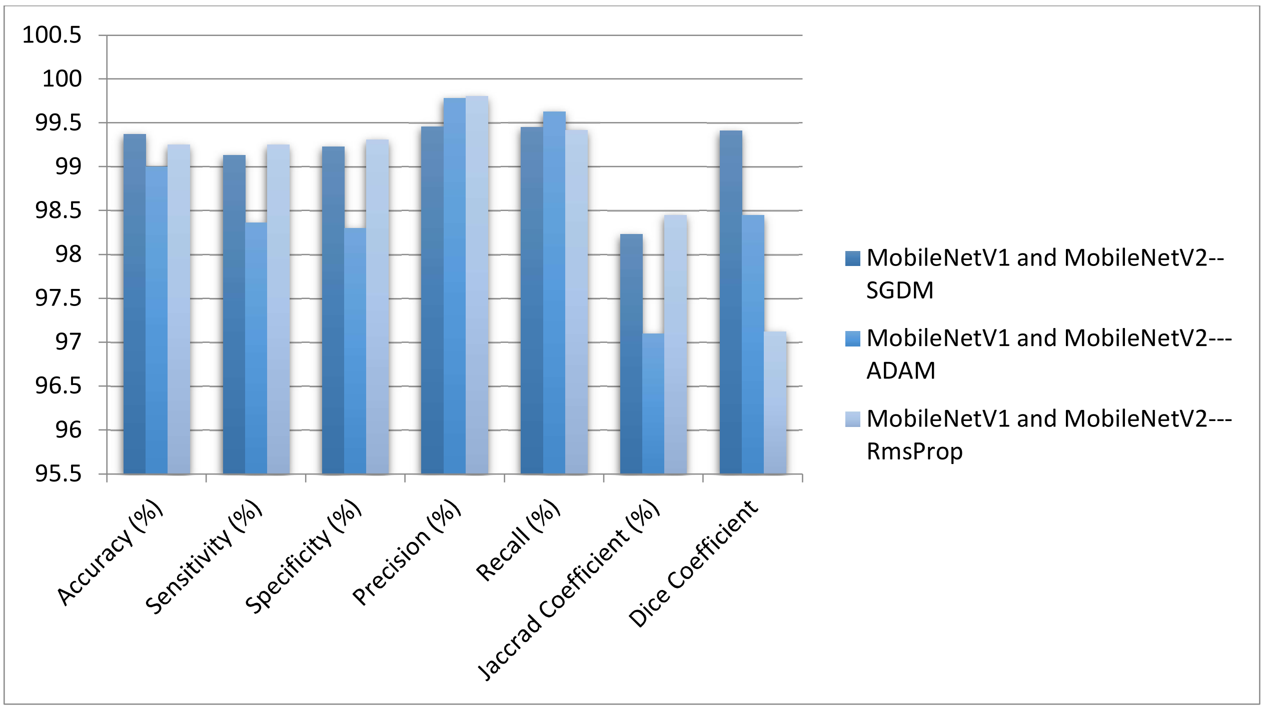

Fig. 3 input image and segmentation image

SGDM (Stochastic Gradient Descent with Momentum) optimization algorithm achieved the highest overall performance with an accuracy of 99.37%. It also performed well in sensitivity, specificity, precision, and recall, showing that it can effectively detect both positive and negative cases with high accuracy.

ADAM optimization algorithm achieved slightly lower accuracy (99.00%) compared to SGDM. However, it still performed well overall and had a high precision of 99.78%, indicating fewer false positives.

RmsProp optimization algorithm achieved an accuracy of 99.25% and performed well in sensitivity, specificity, and precision. However, it had a lower recall (97.12%) compared to the other two algorithms, indicating that it might miss some positive cases.

Table 1 performance of the proposed model with existing work

Studies	Techniques	Accuracy (%)
Khalid El et.al. 2020	InceptionResNet V2	92.18
Julian D et. al. / 2020	Deep CNN based on COVID-Net	91.5
Afshar Shamsi et. al. / 2021	ResNet 50 & SVM classifier	87.9
Abhijit Bhattacharya e.t al. / 2022	VGG-19 and BRISK	96.6
Proposed work	Ensemble of mobilenetv1and mobilenetv2	99.37

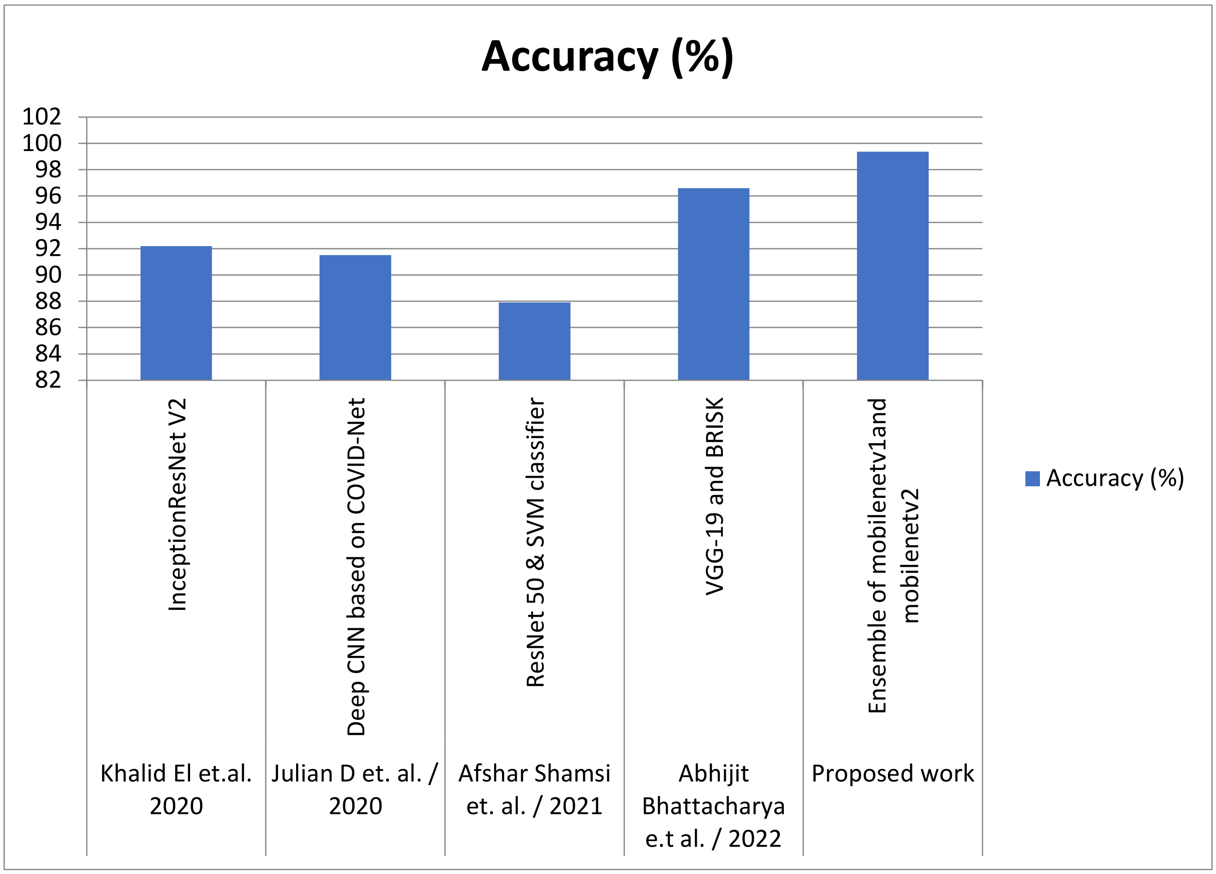

Fig.4 input image and segmentation image

The proposed work, which is an ensemble of MobileNetV1 and MobileNetV2 architectures, achieved the highest accuracy of 99.37%. It outperforms the other studies using different models like ResNet 50, Inception ResNet V2, Deep CNN based on COVID-Net, VGG-19, and BRISK. However, it's essential to note that the proposed work might be using a different dataset or task than the other studies, so direct comparisons may not be entirely fair without additional context. Nonetheless, achieving an accuracy of 99.37% is an impressive result, indicating a promising performance of the proposed ensemble model.

VI CONCLUSION

In conclusion, the proposed system for coronavirus detection using a hybrid of MobileNetV1 and MobileNetV2 represents a promising approach to address the challenges of efficient and accurate COVID-19 screening. By leveraging the advantages of both architectures, the hybrid model combines MobileNetV1's lightweight design with MobileNetV2's improved expressive power. The resulting model is capable of efficiently processing medical imaging data, making it suitable for deployment on mobile devices and resource-constrained environments. Through depthwise separable convolutions and inverted residual blocks, MobileNetV1 and MobileNetV2 extract meaningful features from chest X-ray images, capturing both spatial and channel-wise information. By combining the extracted features through concatenation the hybrid model creates a richer feature representation, enhancing its ability to distinguish between healthy and COVID-19 affected lung images.

The system's training process involves fine-tuning the new fully connected layers on a labeled dataset of chest X-ray images, specifically annotated for COVID-19 cases. The inclusion of data augmentation techniques helps the model generalize better and mitigate overfitting concerns. The hybrid model's lightweight nature enables rapid and efficient deployment, making it ideal for point-of-care applications and remote healthcare settings. Early and accurate detection of COVID-19 can aid healthcare professional’s untimely diagnosis and treatment, potentially mitigating the spread of the virus and improving patient outcomes. However, it is essential to acknowledge that the effectiveness of the proposed system depends on the quality and size of the training dataset and the careful selection of hyperparameters during the fine-tuning process. Additionally, as the COVID-19 pandemic evolves, the system may require updates with newer data and research advancements.

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