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Covid-19 Detection For CT-scan Images Using Transfer Learning Models

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Abstract—COVID-19 is a respiratory illness caused by a virus called SARS-CoV-2 which affected around 455 million people around the world. CT-scan is a medical imaging technique that uses X-rays to create detailed images of the body and which can be used to detect many respiratory diseases. Transfer learning models are a type of machine learning model that are trained on a large dataset of images and which can be used for their already trained ability to extract features from image in other tasks. They can then be used to classify new images with similar features.This paper presents a study of different transfer learning models for the task of classifying chest X-ray images into three classes: COVID-19, pneumonia, and normal. The study was implemented using Python and the dataset used was the COVID-19 Chest X-ray Dataset. The train-test split used was 0.2–0.8. The parameters used to test the models were the precision, recall, accuracy, F1 score, and Matthew's correlation score. Other than these, different optimizers were also compared such as ADAM, SGD with different learning rates of 0.01, 0.001, and 0.0001.The models used in this study are EfficientNetB0, EfficientNetB7, VGG16, and InceptionV3. Out of these models, the most effective model was the EfficientNetB0 model, which achieved an accuracy of 98.6%. This study provides valuable insights into the use of transfer learning for medical image analysis. The results suggest that transfer learning can be used to develop accurate and efficient models that can be used as a secondary option for the diagnosis of COVID-19 using chest X-ray images.

Keywords- TransferLearning,Covid-19pneumonia,CNN,CT-Scan,learning rate.

I. INTRODUCTION

Viral pneumonia and COVID-19 are serious respiratory diseases that can cause significant morbidity and mortality, especially in high-risk populations such as the elderly and those with underlying health conditions[1]. The early and accurate detection of these diseases is crucial in order to prompt effective treatment and reduce the spread of the disease. Computed Tomography (CT) scans and X-ray images are commonly used in the diagnosis of respiratory diseases, including viral pneumonia and COVID-19[1]. These imaging modalities provide valuable information about the structure and function of the lungs, and can often help to detect changes associated with these diseases, such as inflammation, fluid buildup, and consolidation. Various imaging techniques offer important insights into the composition and operation of the lungs and frequently aid in the recognition of changes brought on by these illnesses, such as swelling, inflammation, and consolidation. The aim of a project focused on the detection of viral pneumonia and COVID-19 using CT scan/X-ray images is to develop a machine learning-based algorithm that can accurately and efficiently diagnose these diseases from imaging data[3]. The project would likely involve the collection and labeling of a large dataset of CT scan and X-ray images, the development of a deep learning-based algorithm for image analysis[4], and the evaluation of the performance of the algorithm using a validation dataset. Overall, the successful completion of this project could have a significant impact on the early detection and treatment of viral pneumonia and COVID-19, helping to improve patient outcomes and reduce the spread of the disease.

II. METHODOLOGY

A. Method

Transfer learning is a powerful optimization technique that enables the application of knowledge gained from one task to another task[7]. This is especially helpful for deep learning,

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where gathering enough data for each job can be a considerable difficulty because a large amount of data is needed for training. Transfer learning can be used in a variety of ways to help models perform better on new and related tasks by leveraging previously acquired patterns and representations. In this paper, different CNN transfer learning networks will be utilized, which are pre-trained on the ImageNet dataset with 1000 classes, making them powerful networks that can be fine-tuned for a specific task by adjusting the weights of their last layers. The impact of fine-tuning on various performance parameters, such as accuracy, precision, and recall, will be discussed. The objective is to train these models to classify chest X-ray images as either pneumonic, COVID, or normal. The dataset used for training is obtained from Kaggle.

B. Dataset

The study utilizes a public dataset available on Kaggle called the COVID-19 Radiography Database, which comprises 3616 images of Covid-19 patients, 10200 images of normal patients, and 1345 images with viral pneumonia, all of which are of size 299*299 pixels. It is evident that the provided dataset is biased towards the normal case, given that it has the highest number of images, while the viral pneumonia class has the least number of images, resulting in the most significant variation in that class. To tackle the bias issue of this data only 3616 images from the normal class are chosen to bias.These images are then taken and rescaled to the size of 120×120 to make them easy to process.

C. Transfer Learning

As discussed before, transfer learning is a method where a pretrained model is to be used for our task by further training it using our data so that it works better for our task. Thus, in this paper, models such as VGG16 and InceptionV3 have been selected. All of these networks have been taken without their dense layers(top) which are used to make predictions and are replaced with other dense layers so that they can be used to make predictions for our case[5]. These layers are further trained using this dataset to make predictions on new testing data. To test this network further combinations of training testing data ratios are used to check their performance for these conditions. The paper also includes a comparison of the performance of these models in some cases concerning changes in parameters such as learning rate, optimizer, and callbacks.

D. Model Architecture

CNN model is the most popular choice for feature extraction from image data and to process image data as it reduces the calculations required for the feature extraction[6]. Fig.1 shows the flowchart of the CNN model. To increase the reliability and accuracy of the model transfer learning models such as VGG16 and InceptionV3 models are used. These models are very complex whose architecture is given in figure below, these models are used as convolutional bases. These convolutional bases contain layers like convolutional layers which are used for feature extraction.

Fig.1. Flow chart of the VGG16 CNN model

These layers are used in cascading models with pooling layers such as max pooling and dropout layers which prevent them from overfitting by dropping a certain number of neurons randomly from the model. These convolutional bases are then connected to dense layers which are defined by us with the number of nodes per layer as 512,256,128 for layer 1,2,3 respectively. Every layer from this network uses ReLu activation function, which gives the linear output for input greater than 0 and gives zero output for input less than zero, which makes it the one of the best activation function for deep learning models as it requires the least amount of computations and these models generally have millions of parameters. Only last layer of the fully connected layer has softmax activation function as it is used to predict the output for multiclass classification and output of this layer is in the array format with same number of elements as that of number of labels with indexes containing probability for that index occurring. Thus the output is calculated by taking the label with maximum probability. The Diagram shown below has a general structure for an image classification model with convolutional base showing a general structure of convolutional neural networks to which a fully connected layer which can be defined according to the the requirements of the task to de done. Fully connected layer is shown in format of Type of layer[8], Number of nodes/Neurons, and activation function. For this task, transfer learning models will be employed, which entail stacks of

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convolutional layers and max pooling layers. Some of these layers will be designated as trainable, while others will be marked as not trainable.[9]

E. Parameters used and Methodologies followed

To measure the performance of these models several performance metrics were used which are applicable for multiclass classification model they are listed below: some of the parameters used in comparison are given below

Accuracy: It is the percentage of predictions which our model got right out of the total number of predictions. It is given by

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{T.P+T.N}}{\boldsymbol{T.P+T.N+F.P+F.N}} \quad (1)$$

Precision: Precision measures the models accuracy in predicting the correct positives i.e. it is the ratio of correct positive predictions to total positive predictions[10]. It is given by

$$\boldsymbol{Precision} = \frac{\boldsymbol{T.P}}{\boldsymbol{T.P+F.P}} \quad (2)$$

Recall: Another parameter used to assess the effectiveness of a classification model, particularly in the context of binary classification, is recall,[11] often referred to as sensitivity or true positive rate. It is given by

$$\boldsymbol{Recall} = \frac{\boldsymbol{T.P}}{\boldsymbol{T.P+F.P}} \quad (3)$$

F1 Score: It is the harmonic mean of recall and precision, giving a fair assessment of the model's ability to correctly predict both positive and negative events. It is given by

$$\boldsymbol{F1\ Score} = \frac{\boldsymbol{2 \times recall \times precision}}{\boldsymbol{recall + precision}} \quad (4)$$

Matthew's Correlation Coefficient: MCC gives us the best idea of performance of models for both positive and negative classes.
It is given by

$$\boldsymbol{MCC} = \frac{\boldsymbol{T.N \times T.P - F.N \times F.P}}{\sqrt{\boldsymbol{(T.P+F.P)(T.P+F.N)(T.N+F.P)(T.N+F.N)}}} \quad (5)$$

All of these metrics were used to assess the performance of models trained with different ratios/amount of data to analyze the effect of training data[12] to testing data size and these values were noted to be compared. All of these parameters give us information about different characteristics of the model[13].While comparing the parameters of models, confusion matrices were also plotted to assess class wise prediction accuracy[14]. Total of 4 conditions were checked for different train test splits 0.2-0.8,0.3-0.7,0.4-0.6,0.5-0.5 respectively. In these formulas used the terminologies used are T.P,T.N,F.P,F.N which are true positive, true negatives, false positives and false negatives.[15]

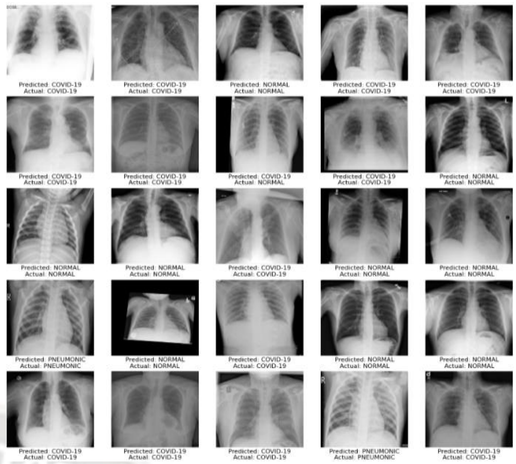

Fig.2. Actual and predicted output for EfficientNetB0 model

Figure 2 shows the output of EfficientNetB0 in terms of image with its actual and predicted output which is shown below the image. Output is calculated for testing data and contains output of 25 images out of which only one of the image is misclassified which shows that model works perfectly, figure also show that some of them are not similarly oriented as others and still model is able to predict the correct output thus concluding that model can also predict output for images with little orientation issues. Here only 25 images were taken from testing data to show the output but in actual testing and training batch size of 32 is taken[16].

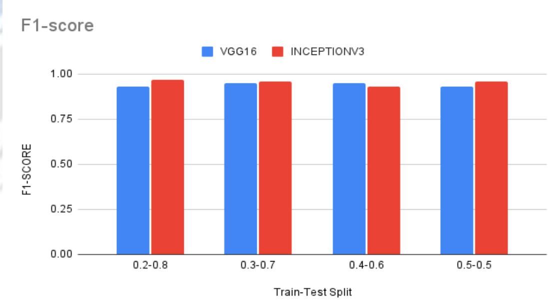

Fig.3(a): Comparison of F1-score of InceptionV3 and VGG16 models with train-test-splits.

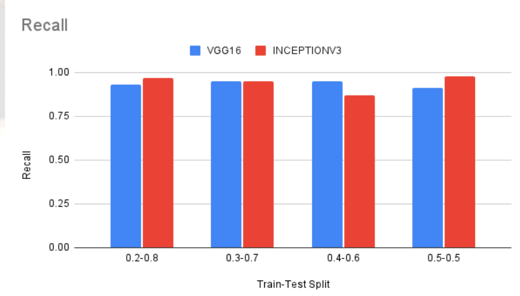

Fig.3(b): Comparison of Recall of InceptionV3 and VGG16 models with train-test-splits.

Based on their F1-Scores and recall scores, the accompanying figure compares the performance of two deep learning models, VGG16 and InceptionV3, on various train-test split ratios. According to the findings, InceptionV3 performs better than

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VGG16 overall in terms of F1-Score, with a range of 0.93 to 0.97 compared to 0.93 to 0.95 for VGG16. While VGG16's recall scores vary from 0.91 to 0.95, InceptionV3's recall scores are higher, ranging from 0.87 to 0.98. It is crucial to remember that both models get comparatively high F1-Scores, demonstrating their accuracy in identifying the photos. Moreover, the difference in performance between the two models is not considerable.[17] This implies that the model selection may be influenced by the particular requirements of the work and the available resources. The train-test split ratio has a significant impact on how well a machine learning model performs. The data in the table demonstrates that while the proportion of testing data tends to decrease, an increase in the proportion of training data tends to improve the F1-Score. This is because the model may learn more effectively and perform better on the test set when there is a larger pool of training data. The outcomes, however, also show that this pattern has a few exceptions. For instance, when the train-test split ratio is 0.4–0.6 for InceptionV3, the recall score drastically drops from 0.95 to 0.87. This implies that improving the proportion of training data alone may not always result in greater performance and that the best train-test split ratio should be chosen based on the unique properties of the dataset and the job at hand.[18]

Fig.4(a): Comparison of Precision of InceptionV3 and VGG16 models with train-test-splits.

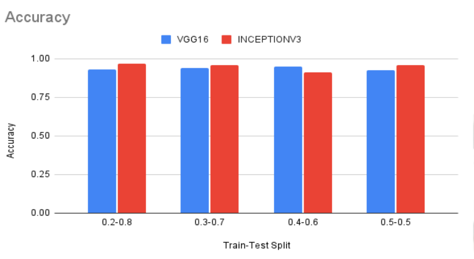

Fig.4(b): Comparison of Accuracy of InceptionV3 and VGG16 models with train-test-splits.

The results displayed in the figure on the left indicate that both VGG16 and InceptionV3 achieve high precision scores across all train-test split ratios. For VGG16, the precision scores range from 0.94 to 0.95, while for InceptionV3, they range from 0.94 to 0.98. InceptionV3 generally achieves higher precision scores than VGG16, indicating that it is better at making accurate positive predictions[19]. Whereas figure on the right indicate that both VGG16 and InceptionV3 achieve high accuracy scores across all train-test split ratios[20]. However, there are some variations in the performance of the models across different splits. For VGG16, the accuracy scores range from 0.93 to 0.95, while for InceptionV3, they range from 0.91 to 0.97. InceptionV3 achieves the highest accuracy score with a train-test split ratio of 0.2-0.8, whereas VGG16 achieves the highest accuracy score with a ratio of 0.4-0.6. The performance metrics of the models seem to be noticeably impacted by the train-test split ratio. Both VGG16 and InceptionV3 show an improvement in accuracy scores as the quantity of training data rises because additional training data enables the models to better understand the patterns in the data and provide more precise predictions. Nonetheless, there are several outliers to this general pattern. For instance, across all train-test split ratios, the precision score for VGG16 remains constant at 0.95. Similarly, when the proportion of training data rises, the accuracy of the models also tends to do so, as more training data enables the models to get a deeper understanding of the patterns in the data and produce more precise predictions. Conversely, there are some circumstances in which a higher percentage of training data may result in subpar performance. For instance, when the train-test split ratio shifts from 0.3-0.7 to 0.4-0.6, the accuracy score for InceptionV3 falls from 0.96 to 0.91. These findings emphasize the need of selecting the train-test split ratio carefully when assessing the effectiveness of machine learning models.[21]

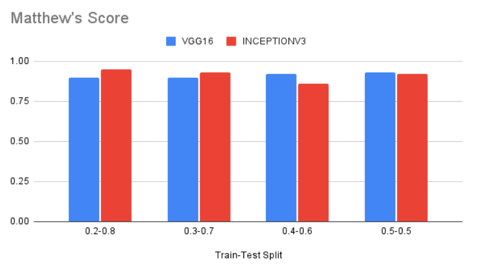

Fig.4 (c):Comparison of Matthew's Score of VGG16 and InceptionV3 models with train-test-splits

The figure shows the MCC scores achieved by two different deep learning models, VGG16 and InceptionV3, on different train-test split ratios. It can be observed that both models achieve relatively high MCC scores, ranging from 0.86 to 0.95. InceptionV3 outperforms VGG16 in terms of MCC score, particularly when the proportion of training data is higher.[22,23,24]

Optimizers are a very important part of model training as they are responsible for updation of the weights based on the gradient of the loss function with respect to weight thus they directly affect how fast and well the model converges to the required accuracy.[25] Equation given below show us how the new weights are calculated based on previous weights, learning rate and loss function. Choice of optimizers is based on multiple factors such as complexity of neural network, complexity of dataset.

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$$W_{new} = W_{old} - \alpha\frac{\delta J(e)}{\delta W} \qquad (6)$$

For the model trained for classification two optimizers are tested which are most widely used these are SGD(stochastic gradient descent) and ADAM (Adaptive moment estimation). These two optimizers have different ways of working. SGD starts working by moving in the negative direction of gradient and takes small steps for each parameter at each timestep which is kept constant whereas ADAM uses different learning rates for all parameters at different timestamps to adapt to the loss function to achieve least loss and highest accuracy with given weights.[26,27]

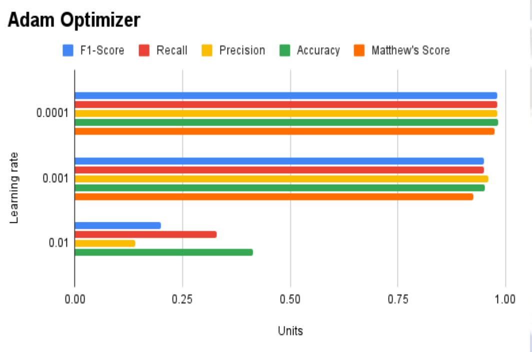

Fig.5(a): Comparison of learning rates with VGG16 of Adam Optimizer.

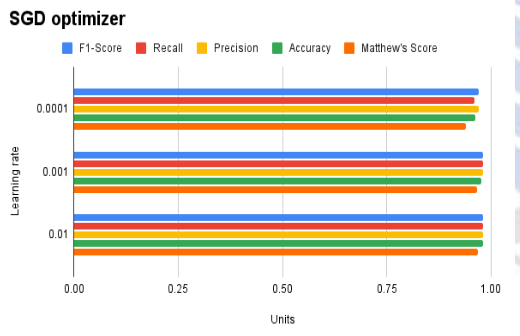

Fig.5(b): Comparison of learning rates with VGG16 of SGD optimizer.

The model with ADAM optimizer performs well on the problem when the learning rate is 0.0001, as evidenced by high F1-Score, Recall, Precision, Accuracy, and Matthew's Score shown in figure 5. The model's performance somewhat declines when the learning rate is raised to 0.001, especially in terms of F1-Score and Recall. The model's performance, however, substantially declines when the learning rate is increased to 0.01, with extremely low F1-Score, Recall, and Precision, suggesting poor performance on the task. Whereas a model with SGD optimizer displays how well a model performs on a classification task using the SGD optimizer at various learning rates[]. The model performs well on the problem when the learning rate is 0.0001, as evidenced by high F1-Score, Recall, Precision, Accuracy, and Matthew's Score. The model performs better when the learning rate is raised to 0.001 and 0.01, which shows that doing so is advantageous in this situation for the F1-Score, Recall, Precision, Accuracy, and Matthew's Score. Overall, SGD performs better on the classification challenge when used as an optimizer with greater learning rates (0.001 and 0.01).[28] Thus it can be said that with this model architecture SGD performance of the model gets better by increasing the learning rate whereas having higher learning rate for Adam optimizer deteriorates the models performance.

The data shows that InceptionV3 outperforms the VGG16 model in all train-test split ratios, with greater performance overall. As evidenced by higher F1-Score, Recall, and Matthew's Score, the InceptionV3 model performs particularly better overall in terms of accurately discriminating between positive and negative events. High Precision ratings for both models show low false positive rates[]. The results show that InceptionV3 outperforms VGG16 for photo categorization tasks, at least in this specific case. While recording this data callbacks were kept on thus this data might not be the most accurate representative of the model as the model might be less trained on the data. These callbacks make sure that the model do not overfit to the data by making sure that training stops when delta starts stagnating.[29]

Based on the available data and its high scores across all criteria, the EfficientnetB0 model appears to perform the best of the models examined. Both the InceptionV3 and ResNet50 models perform admirably, receiving excellent rankings across the board.[30] Although having significantly lower scores across the board, the VGG16 and EfficientnetB7 models nevertheless perform effectively. Effectiveness models are newly designed models based on efficient architectures for best performance, fast processing least requirement of preprocessing the images, it is shown by not having to normalize image pixels as it is done by the model while training itself. Making it more useful for mobile and edge device applications as it reduces data preprocessing which puts a lot of load on the basis of matrix calculations.

III. RESULTS AND DISCUSSION

In this work four parameters are used to compare different models and training methods. These parameters are train-test splits, learning rate of optimizers, type of optimizers, transfer learning models. To compare the performance of different train-test splits, two models, VGG16 and InceptionV3, have been utilized with callbacks on and minimum delta set to 0.001 and patience of 10 epochs. Adam optimizer was used during this entire process with default learning rate of 0.001.Observations were taken for 4 different ratios of train test splits; those were 0.2-0.8,0.3-0.7,0.4-0.6,0.5-0.5. Comparison for learning rate was done on VGG16 model with callbacks being off and while increasing learning rates by 10 times for each observation i.e 0.0001,0.001,0.01. Two different optimizers used were Adam and SGD both of which are widely used optimizers. All the models which were used are VGG16, InceptionV3, EfficientnetB0, EfficientnetB7 and ResNet50. Based on the 5 parameters which were compared for each train test splits in

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according to F1-score the inceptionv3 model with train-test split of 0.2-0.8 has highest f1-score of 0.97 and InceptionV3 model overall outperforms the VGG16 model,while in recall parameter also InceptionV3 model outperformed VGG16 model with split of 0.5-0.5 and recall of 0.98.

TABLE I. Comparison of different transfer learning models

Model	*F1-Score*	*Recall*	*Precision*	*Accuracy*	*Matthew's Score*
VGG16	0.93	0.93	0.93	0.94	0.8960
Inception V3	0.97	0.97	0.98	0.97	0.95
EfficientnetB0	0.99	0.99	0.98	0.9860	0.9775
EfficientnetB7	0.98	0.98	0.98	0.9773	0.9653

Similarly as seen in table 1 in all other parameters such as precision , accuracy and Matthew's score InceptionV3 model outperforms with highest respective values as 0.98,0.97,0.95 VGG16 showing that it is the best model for the given task in a given condition. When comparing the models with learning rates model with lower learning rate performs better as transfer learning model needs to have lower learning learning to not change the weights or filters drastically and maintain them for feature extraction. In case of different optimizers ADAM optimizer works better with lower learning rate and SGD works better with higher learning rate while ADAM with learning rate of 0.0001 works the best, And out of all the transfer learning models compared EfficientNetB0 is best working model. In most of the cases models with callbacks work better but in cases with lower learning rate callbacks help as the model learns better for more number of epochs.

IV. CONCLUSION

In this work different transfer learning methods compare models with different values for their hyperparameters for the purpose of classification of images in different classes such as Covid-19, Pneumonia and Normal. The models which were tested are EfficientnetB0, EfficientnetB7 , ResNet50, VGG16 and InceptionV3 out of all the models as efficient net models are designed on latest architectures and perform best out of all. The squeeze-and-excitation (SE) blocks, swish activation functions, and stochastic depth regularization used by the EfficientNet model further enhance feature representation, decrease overfitting, and increase non-linearity, which further improves the network's performance.. The EfficientNetB0 performs the best with the accuracy of 98.6% on the testing data with the learning rate of 0.01 with Adam as the optimizer and early stopping callbacks on. VGG16 and InceptionV3 models were also tested for different training and testing ratios out of which models with ratio of 0.2-0.8 outperform other models by significant margins as there is more data for training thus reducing the chances of overfitting the model to the given data and as there is more data for training it also increases the validation data giving us the clear idea of how these ratios and performance parameters are related with each other. Other parameters which were compared are the learning rate and optimizers for the VGG16 model with callbacks off in order to see the effect of overfitting as more number of epochs give us the idea of how well the model performs for a large number of epochs. As discussed in the previous section, the model with Adam as optimizer tends to perform better with higher learning rate while model with SGD as optimizer tend to get better with increase in learning rate for these testing conditions. In different parameters and situations which were compared like train test splits different parameters are seen better for different splits such as According to F1-score, the InceptionV3 model outperforms the VGG16 model overall, with a train-test split of 0.2–0.8 having the greatest F1-score of 0.97, and in other parameters also InceptionV3 outperforms VGG16.When comparing the learning rates model with lower learning rate of 0.0001 in case of ADAM optimizer works best with accuracy of 98.36% and in case of SGD optimizer model with higher learning rate of 0.01 works best with accuracy of 96.81%. While comparing the models EfficientNetB0 works best with accuracy of 98.60% followed by EfficientNetB7 with accuracy of 97.73% showing that EfficientNet models which are based on modern architecture work best.

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