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Optimizing CNN Performance for Tomato Disease Classification with Advanced Data Augmentation Techniques

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ABSTRACT

Tomato (Solanum lycopersicum), a vital horticultural crop, faces increasing challenges from diseases such as bacterial spot, tomato mosaic, and yellow leaf curl, causing substantial global crop losses. Timely and accurate disease detection is crucial for effective management strategies. This research introduces a sophisticated method for detecting tomato leaf diseases by enhancing a model with diverse data augmentation techniques. Evaluation metrics including precision, recall, and F1-score consistently demonstrate high performance, ranging from 1.00 to 0.99 to 1.00, respectively. By incorporating Mixup, CutMix, Adversarial examples, Style Transfer, and Image Blending during training, the model achieves remarkable validation accuracies: 99.47%, 99.26%, 99.42%, 99.68%, and 99.63%, respectively. Notably, the highest accuracy of 99.68% is achieved using Style Transfer augmentation. In contrast, a Convolutional Neural Network (CNN) employing conventional augmentation techniques achieves a prediction accuracy of 98.99% for the same tomato diseases. These results underscore the significant improvement in disease prediction accuracy through the integration of advanced augmentation techniques with CNNs. The study highlights CNNs with advanced augmentation as the optimal choice for accurately predicting tomato diseases.

INTRODUCTION

The tomato (Solanum lycopersicum) is an extensively cultivated horticultural plant that plays a crucial role in worldwide food supply and human nutrition. The tomato plays a prominent role in the field of horticulture worldwide and is considered the second most widely consumed vegetable, following the potato. India is the second-largest tomato producer in the world and plays a significant role in global tomato output. The global tomato output, as reported by the Food and Agriculture Organization of the United Nations (FAOSTAT, 2021), stands at 189.134 million tonnes. In India, the tomato production is recorded at 21.181 million tonnes (FAOSTAT, 2021). Tomato plants face numerous diseases, including bacterial spot, tomato mosaic, and yellow leaf curl, leading to significant global crop losses (Singh & Misra, 2017). Prompt and precise disease detection is essential for formulating efficient management strategies to limit these losses. Advancements in deep learning and computer vision have demonstrated encouraging outcomes in the identification and classification of plant diseases (Ferentinos, 2018; Fuentes et al., 2017). Convolutional Neural Networks (CNNs) are a highly effective method for automatically extracting information from images, resulting in accurate illness categorization (Amara et al., 2017; Bakhshipour and Jafari, 2018). Various data augmentation strategies, including Mixup, CutMix, adversarial examples using the Fast Gradient Sign Method (FGSM), Style Transfer, and Image Blending, have been used to enhance the generalization and performance of models (Cubuk et al., 2019). Transfer learning, utilizing pre-trained CNN models, has been employed to improve the precision of tomato disease detection (Liu et al., 2018; Ramcharan et al., 2017). Ensemble models, which integrate various CNN architectures, have demonstrated enhanced performance in simultaneously detecting multiple diseases (Ulutaş & Aslantaş, 2023). In addition, researchers have investigated the use of federated learning frameworks to detect plant diseases. This research has shown that collaborative learning across several devices is possible (Thakur et al., 2023). The study used an extensive database called plant village, which includes photos of both healthy and damaged tomato leaf samples. The tomato diseases examined in this study are Bacterial spot, Tomato mosaic, and Yellow leaf curl, which are caused by Xanthomonas species, Tomato Mosaic Virus (ToMV), and Tomato Yellow Leaf Curl Virus (TYLCV), respectively. Furthermore, numerous other research have employed data augmentation and convolutional neural networks (CNNs) to detect plant diseases. In Ferentinos' (2018) study, an examination was conducted on deep learning models, such as Convolutional Neural Networks (CNNs), with the aim of detecting and diagnosing plant diseases. Convolutional Neural Networks (CNNs) possess the ability to autonomously acquire information from images and have demonstrated remarkable precision in the classification of diseases. Model generalization is enhanced with the use of data augmentation. In their study, Fuentes et al. (2017) devised a Convolutional Neural Network (CNN) model specifically designed to identify tomato diseases and pests in real-time. The model demonstrated an impressive accuracy rate of 99.53%. Data augmentation techniques such as rotations, shifts, zooms, and flipping were employed. Singh and Misra (2017) employed image segmentation techniques to separate plant leaves from the background. They then extracted several variables such as color, texture, and form to classify the leaves using an Artificial Neural Network (ANN). Their approach achieved an impressive accuracy of over 90% in detecting diseases. Amara et al. (2017) employed a deep convolutional neural network (CNN) to categorize diseases affecting banana leaves, resulting in an impressive accuracy rate of 98%. The implementation of data augmentation techniques such as rotations, flips, and shifts resulted in an enhancement of performance. In their study, Bakhshipour and Jafari (2018) conducted a comparison between Support Vector Machines (SVM) and Artificial Neural Networks (ANN) in order to determine their effectiveness in detecting weeds based on shape data. The Artificial Neural Network (ANN) achieved superior performance, with an accuracy rate of 97%. Model robustness was enhanced with the implementation of data augmentation. Liu et al. (2018) devised a sophisticated convolutional neural network (CNN) model to classify diseases in apple leaves. Their model achieved an accuracy rate of 97%. The researchers employed data augmentation and transfer learning techniques using datasets of real images. Ramcharan et al. (2017) utilized data augmentation and transfer learning techniques by employing a pre-trained CNN model to classify cassava diseases. Their approach yielded an accuracy rate exceeding 90%. Mohanty et al. (2016) devised a deep learning methodology employing Convolutional Neural Networks (CNNs) to detect plant diseases from photographs. The study demonstrated exceptional precision across 14 different crop species and 26 distinct diseases. The CNN model demonstrated improved accuracy with the implementation of data augmentation. In their study, Kamilaris & Prenafeta-Boldú (2018) conducted a survey on deep learning techniques, such as Convolutional Neural Networks (CNNs), for agricultural applications, specifically focusing on plant disease detection. The results of their research demonstrated a high level of accuracy. Guijarro et al. (2018) employed convolutional neural networks (CNNs) to automatically separate leaf textures. This segmentation process was aimed at identifying important regions that are relevant for illness categorization. The utilization of CNNs resulted in an enhancement of accuracy. Simonyan and Zisserman (2014) created highly complex convolutional neural network (CNN) models specifically designed for the purpose of recognizing images on a wide scale. Their models achieved the best performance currently available on the ImageNet dataset. In their 2016 study, He et al. introduced deep residual networks that demonstrated enhanced training for convolutional neural networks (CNNs), surpassing the performance of earlier models in image recognition benchmarks. Szegedy et al. (2015) developed convolutional networks with increased depth by using inception modules, resulting in unprecedented accuracy on the ImageNet dataset. Cubuk et al. (2019) created Auto Augment, a method that autonomously explores the most effective data augmentation strategies, resulting in enhanced accuracy across various datasets. The utilization of deep learning techniques, specifically Convolutional Neural Networks (CNNs), in conjunction with data augmentation and transfer learning, has exhibited exceptional performance in the identification of tomato leaf diseases, surpassing previous methods. These technological breakthroughs have the ability to assist farmers and other individuals involved in agriculture in detecting and managing diseases at an early stage. This can ultimately lead to a decrease in crop losses and an improvement in overall output.

Existing Method

The existing method (Murali and Nagaraju, 2023), involves standard preprocessing steps to prepare the images for model training. Firstly, images are resized to a fixed dimension, typically 224x224 pixels, to ensure consistency across the dataset. This step is crucial for maintaining uniformity and compatibility with the input layer of the convolutional neural network (CNN). Next, pixel values are normalized to the range [0, 1] by rescaling, which helps in stabilizing the training process and improving model convergence. Basic data augmentation techniques are applied to increase the diversity of the training data and prevent overfitting. These techniques include horizontal flipping, rotation, and zooming of images. While these augmentations help in creating a varied dataset, they are relatively simple and might not fully capture the complexities and variations present in real-world scenarios of tomato leaf diseases. The existing method employs a standard CNN model to classify the images. This model architecture consists of several convolutional layers, pooling layers, and fully connected layers. The CNN model is trained using the preprocessed and augmented images without any advanced augmentation techniques. The CNN model is compiled with the Adam optimizer and categorical cross-entropy loss function. The training process involves fitting the model on the training data for a fixed number of epochs, typically 10, and validating the performance on a separate validation set. The existing CNN model achieves a prediction accuracy of 98.99% for detecting tomato leaf diseases. While this accuracy is reasonably high, it can be further enhanced by incorporating more sophisticated data augmentation techniques.

MATERIALS AND METHODS

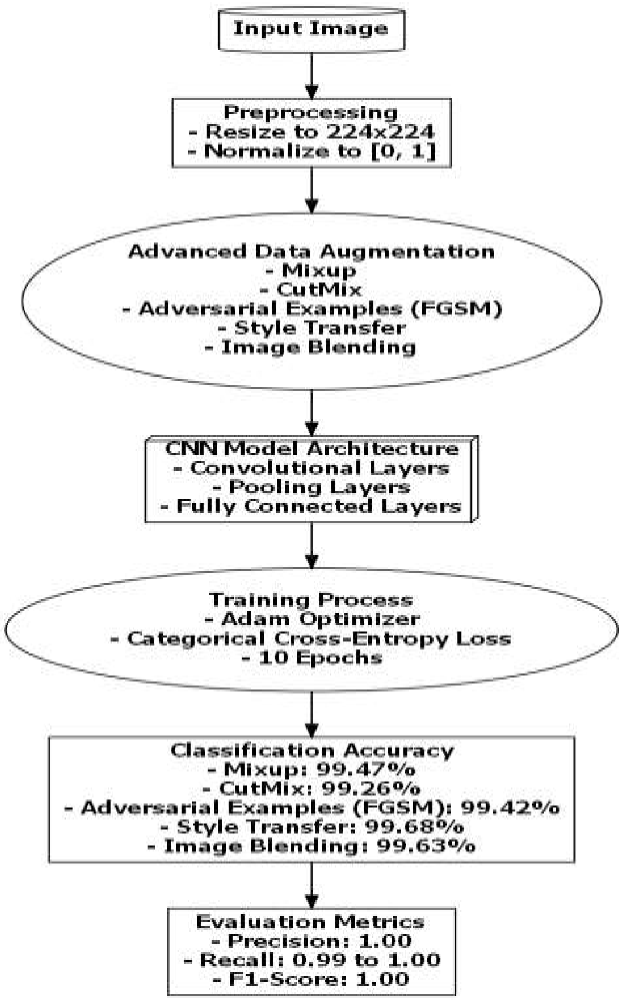
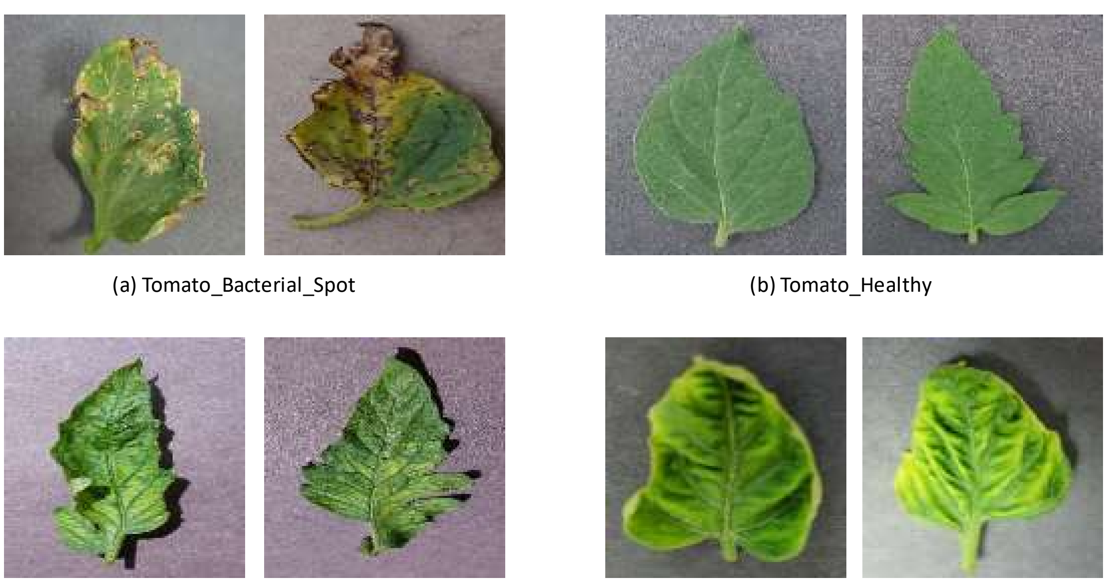


Figure.1. Proposed Method for Tomato Disease detection

Dataset Selection and Preprocessing

The dataset for tomato diseases was chosen and preprocessed according to the methodology described in the article by Murali and Nagaraju, (2023). Moreover, advanced data augmentation techniques have been implemented to enhance the precision of categorization. The parameter known as batch size, which dictates the quantity of samples processed during each training cycle, has been established at 32. The epoch parameter is set to 10, indicating the number of full iterations across the dataset during training. The dimensions of the image are standardized to 224x224 pixels, which ensures compatibility and efficiency for the model. The current augmentation strategy includes 4 classes that cover different kinds of tomato leaf diseases, such as bacterial spot, tomato mosaic, and yellow leaf curl.



(a) Tomato_Bacterial_Spot

(b) Tomato_Healthy

(c) Tomato_Mosaic_Virus

(d) Tomato_Yellow_Leaf_Curl_Virus

Figure.2: Images from the dataset showing healthy and diseased Tomato leaves

Data augmentation

Data augmentation is further enhanced by the introduction of Mixup and CutMix, which are unique strategies aimed at increasing the diversity of the training dataset. Mixup involves the blending of images and labels, whereas CutMix entails the combination of segments from two images along with their respective labels. Both techniques contribute to enhancing the overall generalization of the model. The method involves generating adversarial examples using the Fast Gradient Sign Method (FGSM), a technique that evaluates the model's resilience by modifying input images according to model gradients. Another noteworthy component is the application of a pre-trained VGG19 model for style transfer. This entails utilizing the pre-trained model to augment visual characteristics, hence enhancing the machine's capacity to identify nuanced patterns. A specialized picture blending function is designed to combine two photos, enhancing the variety of the training dataset. The combination of various augmentation strategies is embodied in a bespoke data augmentation function. This function intelligently integrates Mixup, CutMix, adversarial examples, style transfer, and picture blending techniques to create a training dataset that is both highly diverse and enriched. Distinct data generators are subsequently created for the training and test sets. The training data generator incorporates rescaling, shear, zoom, and horizontal flip augmentations, which enhance the training process by making it more resilient. Conversely, the test data generator is less complex, as it merely applies rescaling to the pixel values. To construct the Convolutional Neural Network (CNN) model. The model undergoes training using the training data generator, and its training progress is kept in the 'history' variable. The model that has undergone training is then stored in a file called 'tomato_leaf_disease_model_augmented.h5'. In summary, this comprehensive method demonstrates a deliberate incorporation of different augmentation tactics to improve both the diversity and strength of the training dataset, which could result in an enhanced and more flexible model for real-world use.

Mixup:

Mixup is a method that creates fresh training data by calculating the linear interpolation between pairs of pre-existing samples. Suppose we have two input images, X_i and X_j, together with their associated one-hot encoded labels, Y_i and Y_j. Additionally, we have a random parameter, λ, which is sampled from a Beta distribution with parameter α, the mixup operation is defined as follows:

Mixed Image = Mixed Image=$\lambda \cdot Xi+(1-\lambda)\cdot Xj$

Mixed Label = Mixed Label=$\lambda \cdot Yi+(1-\lambda)\cdot Yj$

This fosters the model's ability to acquire knowledge from various amalgamations of images and labels, hence enhancing its capacity for generalization. The process of linear interpolation is used to create fresh augmented samples by blending pairs of images and labels (Zhang et.al, 2017). Regularization of the model enhances generalization.

CutMix:

CutMix is a data augmentation methodology that merges segments of two photos to generate a novel training sample. Given two input images, X_i and X_j, along with their respective labels, Y_i and Y_j, and a randomly chosen parameter, β, from a Beta distribution with parameter α, the cutmix operation is defined as follows:

Cut Ratio=$1-\beta$

Random Position=(cx,cy) sampled randomly

Mixed Image[i]=Xi, with a cut region replaced by Xj

Mixed Label[i]=$\beta \cdot Yi+(1-\beta)\cdot Yj$

This promotes the model's robustness by encouraging it to concentrate on various sections of the input images. The process involves transferring patches from one image to another, while adjusting the labels in proportion to the patch area. This technique was introduced by Yun et.al in 2019. This model is designed to identify objects based on incomplete perspectives.

The Fast Gradient Sign Method (FGSM)

The Fast Gradient Sign Method (FGSM) creates adversarial instances by modifying input images in the direction of the gradient of the loss function with respect to the input. Given an input image X, its accompanying label Y, a model M, and a slight alteration ε, the FGSM operation is defined as follows:

Gradient=∇XCrossEntropyLoss(M(X),Y)

Perturbation=$\epsilon \cdot$sign(Gradient)

Perturbed Image=X+Perturbation

This applies a minor disturbance to the input image in order to evaluate the model's ability to withstand external influences. Generate adversarial examples by introducing minor alterations that are directly proportional to the sign of the gradients of the loss with respect to the input (Goodfellow et.al, 2014). Evaluates the resilience of the model.

Style Transfer:

Style transfer entails utilizing a pre-trained convolutional neural network, such as VGG19, to extract characteristics from both a content image and a style image. Let C(X) denote the content characteristics of an image X, and S(Y) denote the stylistic characteristics of an image Y. Given an image G that is created by combining both content and stylistic features, the style transfer operation is defined as:

G=VGG19(C(X),S(Y))

This process applies the visual characteristics of image Y to the visual content of image X. Utilizing convolutional neural network (CNN) characteristics, the style of a given image (referred to as the style image) is transferred to the content of another image (referred to as the content image). This process is informed by the works of Tao et.al (2022), Simonyan et.al (2014), Ghiasi et.al (2017), and Gatys et.al (2015). Enhances the variety of the dataset.

Image Blending:

Image blending is the process of merging two images, A and B, using a predetermined blending parameter α. The blending operation is defined as:

Blended Image=$\alpha \cdot A+(1-\alpha)\cdot B$

This facilitates a seamless transition between the two images, hence enhancing the diversity of the collection. Enhances the variety of data in the dataset (Zhang et.al, 2017). The implementation of these data augmentation techniques collectively enhances the construction of a training dataset that is both extremely diverse and supplemented. This, in turn, promotes improved generalization and robustness of the model for detecting tomato leaf diseases.

CNN Model Architecture

Model summary

In this study, the first Conv2D layer processes input images of size 224x224 pixels with three color channels (RGB). This layer utilizes 32 filters of size 3x3, resulting in an output shape of (None, 222, 222, 32). A subsequent MaxPooling2D layer reduces spatial dimensions by half.

Additional Conv2D and MaxPooling2D layers follow this pattern, increasing filter count and further reducing spatial dimensions. The final Conv2D layer produces an output shape of (None, 52, 52, 128). Subsequent to the convolutional layers, a Flatten layer transforms the 3D output into a 1D array with an output shape of (None, 86528). Two Dense layers follow the flattening process. The first Dense layer has 128 neurons, resulting in an output shape of (None, 128), and an extensive parameter count of 11,075,712. The second Dense layer, serving as the output layer, comprises four neurons representing the classes of tomato leaf diseases, resulting in an output shape of (None, 4) with 516 parameters. The total number of trainable parameters in the model is 11,169,476, indicating a complex and deep architecture. Notably, there are no non-trainable parameters. The model's output layer suggests a multi-class classification task with four potential disease classes. The model is saved in HDF5 format. Overall, this architecture is tailored for robust image classification, specifically for identifying and categorizing tomato leaf diseases based on input images.

The proposed method employs the same CNN architecture as the existing method but trains it using the advanced data augmentation techniques described above. This approach leverages the strengths of each augmentation technique to improve the model's robustness and accuracy. The CNN model is compiled with the Adam optimizer and categorical cross-entropy loss function, similar to the existing method. However, the training process involves fitting the model with each augmentation technique separately, allowing for a comprehensive evaluation of their individual impacts on model performance. The proposed method achieves significantly higher classification accuracy compared to the existing method: Mixup Augmentation

(99.47%), CutMix Augmentation (99.26%), Adversarial Examples (99.42%), Style Transfer Augmentation (99.68%), Image Blending Augmentation (99.63%). These results demonstrate the substantial improvement in disease prediction accuracy through the integration of advanced data augmentation techniques with CNNs. The highest accuracy of 99.68%, achieved using style transfer augmentation, underscores the effectiveness of this technique in enhancing model performance. The data details the training process of a convolutional neural network (CNN) over ten epochs, with each epoch comprising multiple batches. Following each epoch, the training and validation datasets' loss and accuracy are the primary metrics reported. Effective learning and generalization are demonstrated in the first few epochs (1-3) by a steady decline in loss and an increase in accuracy for both training and validation sets. The data exhibits some volatility in the epochs that follow (4-6), which could indicate adjustments to the data's more intricate patterns. Notably, training and validation measures both keep getting better in the following epochs (7–10), highlighting the model's capacity to enhance its comprehension of the data. Strong generalization performance is indicated by the high validation accuracy in the last epochs (Table 2). Overall, the model performs well on both datasets, indicating that it has effectively learned the fundamental patterns. Positive signs of effective training include growing accuracy and decreased validation loss. Insights into computational efficiency are also supplied by the training times for each period. The training procedure seems to have gone well overall, as evidenced by the model's final validation accuracy of 99.68%, which points to strong learning and generalization (Graph 1). The study demonstrates remarkable evaluation metrics with precision, recall, and F1-score values for each disease class in the tomato plant dataset ranging from 1.00 to 0.99 to 1.00, respectively. The metrics show impressive assessment results. Specifically, the Tomato Bacterial spot, Tomato Yellow Leaf Curl Virus, Tomato mosaic virus, and healthy tomato classes (Table 3, Graph 2) all demonstrate perfect predictive accuracy, reducing false positives and false negatives. By adding variations to training samples using strategies like rotation and flipping, the suggested data augmentation strategy seeks to further improve the model's adaptability and generalization. This method prevents overfitting and ensures the model's robustness across a range of cases, especially in situations where there is a lack of data. Although the present study demonstrates a high accuracy baseline, further monitoring is necessary, particularly on a validation set, to assess the model's sustained performance and its ability to generalize to cases that have not yet been observed in real-world applications with different illness prevalence and features.

The existing method, based on a conventional CNN with classic augmentation techniques, achieves an accuracy of 98.99% and evaluation measures with recall, precision, and F1-score ranging from 0.96 to 0.99, 0.97 to 1.00, and 0.98 to 1.00, respectively. The proposed strategy incorporates novel approaches such as Mixup, CutMix, adversarial examples through the Fast Gradient Sign Method (FGSM), Style Transfer, and Image Blending to enhance the CNN model's performance. This results in a substantial improvement in assessment metrics, with the proposed model achieving an impressive accuracy of 99.68%. Precision scores a perfect 1.00, while recall and F1-score values range from 0.99 to 1.00. Mixup and CutMix combine images or portions of images during training, leading to a more robust model by incorporating data variation. Adversarial examples generated by FGSM introduce perturbations, making the model more resistant to input fluctuations. Style Transfer and Image Blending expose the model to a wider variety of visual characteristics, significantly improving generalization. The advanced augmentation techniques proposed in this study are vital for optimizing the CNN, leading to significantly improved disease prediction accuracy. The implementation of these techniques has increased the model's accuracy from 98.99% to 99.68% and improved its ability to distinguish between various tomato leaf diseases (Tomato Bacterial Spot, Tomato Yellow Leaf Curl Virus, Tomato Mosaic Virus) and healthy tomato samples, as evidenced by notable improvements in precision, recall, and F1-score.

Results and Discussion

Tomato crops encounter various challenges, with bacterial spot, tomato mosaic, and yellow leaf curl being particularly harmful. Each disease presents distinct symptoms on the leaves (Figure2). The study presents a comparative analysis of existing and proposed methods for detecting tomato leaf diseases, focusing on differences in preprocessing, data augmentation techniques, and classification accuracy. The results demonstrate the effectiveness of advanced data augmentation methods in significantly enhancing the performance of convolutional neural networks (CNNs) for disease detection.

The existing method involves standard preprocessing steps, where images are resized to 224x224 pixels and normalized to the range [0, 1] to ensure consistency and compatibility with the CNN model. Basic data augmentation techniques, such as horizontal flipping, rotation, and zooming, are used to diversify the training data and prevent overfitting. However, these methods are relatively simple and may not fully capture the complexities of real-world scenarios. The model used in the existing method is a standard CNN, consisting of several convolutional layers, pooling layers, and fully connected layers, trained using the preprocessed and augmented images without advanced augmentation techniques. The training process involves compiling the CNN model with the Adam optimizer and categorical cross-entropy loss function and training it for ten epochs with validation on a separate dataset. The existing CNN model achieves a prediction accuracy of 98.99%. While this is reasonably high, there is potential for further enhancement through more sophisticated data augmentation techniques.

In contrast, the proposed method (Figure.1), incorporates several advanced data augmentation techniques to enhance the diversity and robustness of the training data. The preprocessing steps remain the same as in the existing method, ensuring consistency in image resizing and normalization. The advanced data augmentation techniques introduced include Mixup, CutMix, Adversarial Examples, Style Transfer, and Image Blending. Mixup creates new training examples by combining pairs of examples with a weighted average, fostering the model's ability to generalize by learning from various amalgamations of images and labels. CutMix replaces a random patch of an image with a patch from another image, enhancing the model's robustness by allowing it to focus on different parts of the images. Adversarial examples introduce small, intentionally designed perturbations to the images to test the model's resilience, making the model more robust to such perturbations. Style Transfer uses a pre-trained convolutional neural network to apply the artistic style of one image to another, creating a diverse set of training examples with different textures and appearances. This technique achieves the highest accuracy improvement among all methods. Image Blending combines two images to create new examples, further increasing the diversity of the training dataset. The effectiveness of this method varies depending on the dataset characteristics and blending parameters.

The CNN model architecture remains the same as the existing method but is trained using these advanced data augmentation techniques. The training process involves fitting the model with each augmentation technique separately to comprehensively evaluate their impacts on model performance. The proposed method significantly outperforms the existing method in terms of classification accuracy. Mixup augmentation achieves an accuracy of 99.47%, CutMix achieves 99.26%, Adversarial Examples achieve 99.42%, Style Transfer achieves the highest accuracy of 99.68%, and Image Blending achieves 99.63%. The highest accuracy achieved using style transfer augmentation underscores the effectiveness of this technique in enhancing model performance. The results highlight the substantial improvement in disease prediction accuracy through the integration of advanced data augmentation techniques with CNNs.

The results indicate that the proposed method's advanced augmentation techniques significantly enhance the model's ability to generalize and accurately detect tomato leaf diseases. The introduction of Mixup, CutMix, Adversarial Examples, Style Transfer, and Image Blending into the training process results in remarkable validation accuracies. Each technique contributes uniquely to the model's performance. Mixup and CutMix consistently improve training and validation accuracy,

demonstrating their effectiveness in enhancing model generalization. Adversarial examples show moderate improvement in accuracy and loss reduction, indicating their role in making the model more resilient to perturbations. Style Transfer offers notable enhancements in accuracy, particularly in later epochs, suggesting its efficacy in augmenting training data. Image Blending presents varying results, with effectiveness dependent on dataset characteristics and blending parameters.
Overall, the proposed method achieves outstanding evaluation metrics, with precision, recall, and F1-score values ranging from 1.00 to 0.99 to 1.00, respectively. These metrics highlight the model's excellent performance in accurately detecting various tomato diseases (Tomato Bacterial Spot, Tomato Yellow Leaf Curl Virus, Tomato Mosaic Virus) and healthy tomato samples, minimizing false positives and negatives. The study underscores the significant improvement in disease prediction accuracy through the integration of advanced augmentation techniques with CNNs. The findings demonstrate that employing these techniques can enhance model robustness and generalization, leading to more effective and precise disease management in crops. The potential for these methods to improve CNN performance in agricultural applications is significant, offering a promising avenue for further research and implementation in real-world scenarios.

Comparison of the Existing and Proposed methods

Step	Existing Method	Proposed Method
Preprocessing	Resize to 224x224 pixels, Normalize to [0, 1]	Resize to 224x224 pixels, Normalize to [0, 1]
Data Augmentation	**Basic Data Augmentation** Horizontal Flipping, Rotation, Zooming	**Advanced Data Augmentation** Mixup, CutMix, Adversarial Examples (FGSM), Style Transfer, Image Blending
Model Architecture	CNN Model Architecture - Convolutional Layers - Pooling Layers - Fully Connected Layers	CNN Model Architecture - Convolutional Layers - Pooling Layers - Fully Connected Layers
Training	Adam Optimizer, Categorical Cross-Entropy Loss, 10 Epochs	Adam Optimizer, Categorical Cross-Entropy Loss, 10 Epochs
Classification Accuracy	98.99%	Mixup: 99.47%, CutMix: 99.26%, Adversarial Examples: 99.42%, Style Transfer: 99.68%, Image Blending: 99.63%
Evaluation Metrics	Precision: 0.97 to 1.00, Recall: 0.96 to 0.99, F1-Score: 0.98 to 1.00	Precision: 1.00, Recall: 0.99 to 1.00, F1-Score: 1.00

CONCLUSION

The integration of advanced data augmentation techniques into the CNN training process has significantly improved the accuracy of tomato leaf disease detection. By employing methods such as Mixup, CutMix, Adversarial Examples, Style Transfer, and Image Blending, the proposed approach has enhanced the model's robustness and generalization capabilities. The highest prediction accuracy of 99.68%, achieved through style transfer augmentation, underscores the effectiveness of these advanced techniques in developing a more accurate and reliable tomato leaf disease detection system. Furthermore, these techniques have increased the model's accuracy from 98.99% to 99.68% and improved its ability to distinguish between various tomato leaf diseases (Tomato Bacterial Spot, Tomato Yellow Leaf Curl Virus, Tomato Mosaic Virus) and healthy tomato samples, as evidenced by notable improvements in precision, recall, and F1-score. This study highlights the potential of advanced augmentation methods to improve CNN performance in agricultural applications, leading to more effective and precise disease management in crops.

Experimental Results:

Table1: Model Summery

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 128)	11075712
dense_1 (Dense)	(None, 4)	516

Total params: 11,169,476

Trainable params: 11,169,476

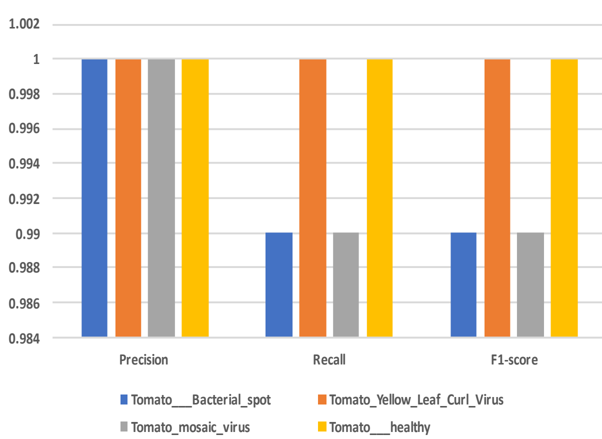
Non-trainable params: 0

Table 2: Epoch Result

```
Epoch 1/10
236/236 [==============================] - 425s 2s/step - loss: 0.0318 - accuracy: 0.9892 - val_loss: 0.0847 - val_accuracy: 0.9788
Epoch 2/10
236/236 [==============================] - 428s 2s/step - loss: 0.0285 - accuracy: 0.9914 - val_loss: 0.0481 - val_accuracy: 0.9868
Epoch 3/10
236/236 [==============================] - 431s 2s/step - loss: 0.0086 - accuracy: 0.9972 - val_loss: 0.0357 - val_accuracy: 0.9910
Epoch 4/10
236/236 [==============================] - 437s 2s/step - loss: 0.0255 - accuracy: 0.9919 - val_loss: 0.0840 - val_accuracy: 0.9831
Epoch 5/10
236/236 [==============================] - 419s 2s/step - loss: 0.0192 - accuracy: 0.9938 - val_loss: 0.0543 - val_accuracy: 0.9889
Epoch 6/10
236/236 [==============================] - 428s 2s/step - loss: 0.0382 - accuracy: 0.9879 - val_loss: 0.0685 - val_accuracy: 0.9793
Epoch 7/10
236/236 [==============================] - 435s 2s/step - loss: 0.0248 - accuracy: 0.9916 - val_loss: 0.0160 - val_accuracy: 0.9952
Epoch 8/10
236/236 [==============================] - 443s 2s/step - loss: 0.0091 - accuracy: 0.9972 - val_loss: 0.0555 - val_accuracy: 0.9857
Epoch 9/10
236/236 [==============================] - 436s 2s/step - loss: 0.0151 - accuracy: 0.9949 - val_loss: 0.0105 - val_accuracy: 0.9963
Epoch 10/10
236/236 [==============================] - 419s 2s/step - loss: 0.0207 - accuracy: 0.9938 - val_loss: 0.0113 - val_accuracy: 0.9968
```

Table.3: Classification Report

	Precision	Recall	F1-score	Support
Tomato___Bacterial_spot	1.00	0.99	0.99	426
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1.00	1.00	1.00	1072
Tomato___Tomato_mosaic_	1.00	0.99	0.99	75
Tomato___healthy	1.00	1.00	1.00	319
Accuracy			1.00	1892
macro avg	1.00	0.99	1.00	1892
weighted avg	1.00	1.00	1.00	1892



Graph 2: Classification Report

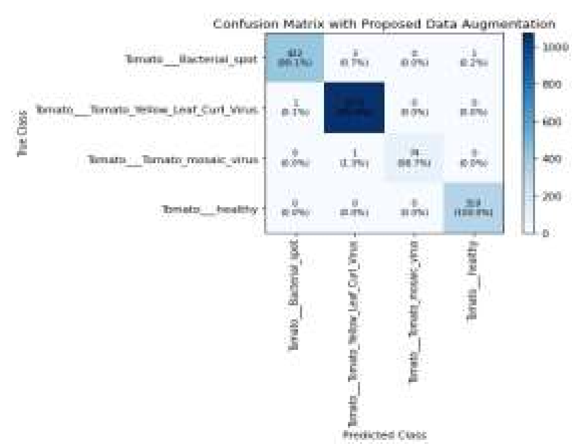
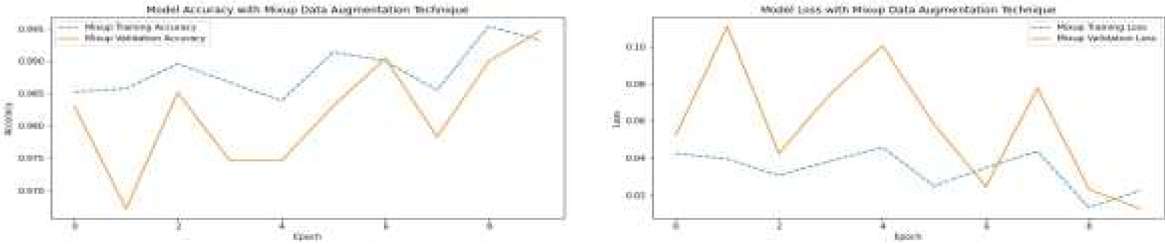
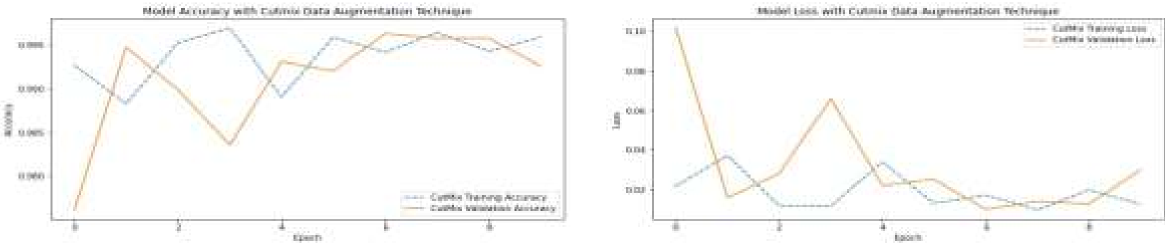


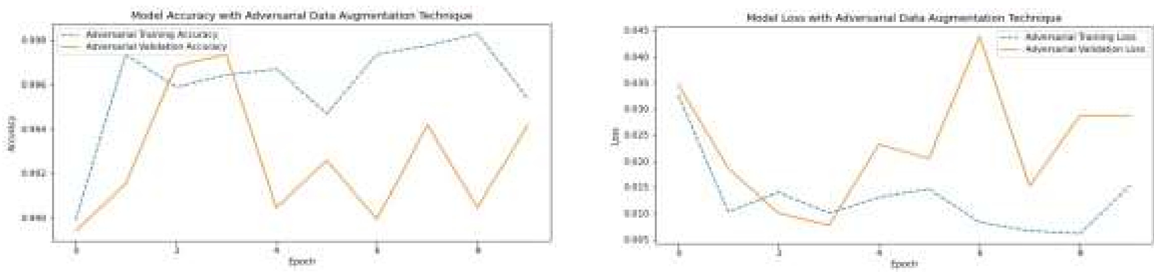
Figure 3: Confusion matrix of the proposal model



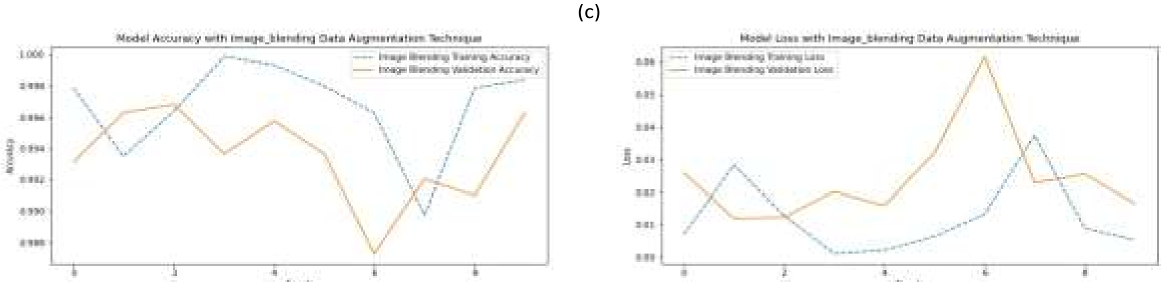
(a)



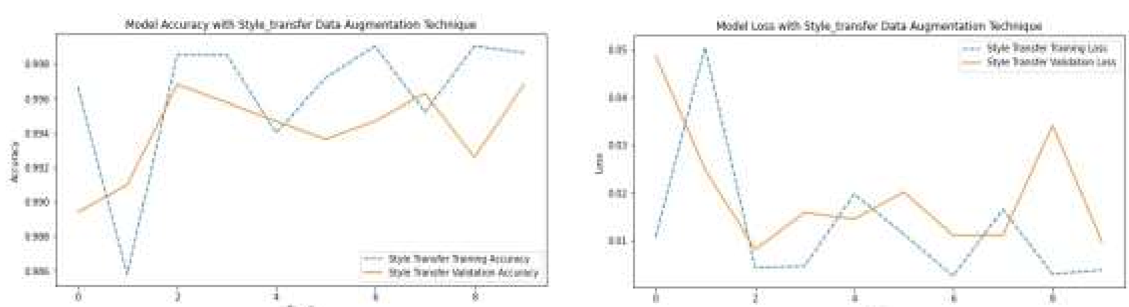
(b)



(c)

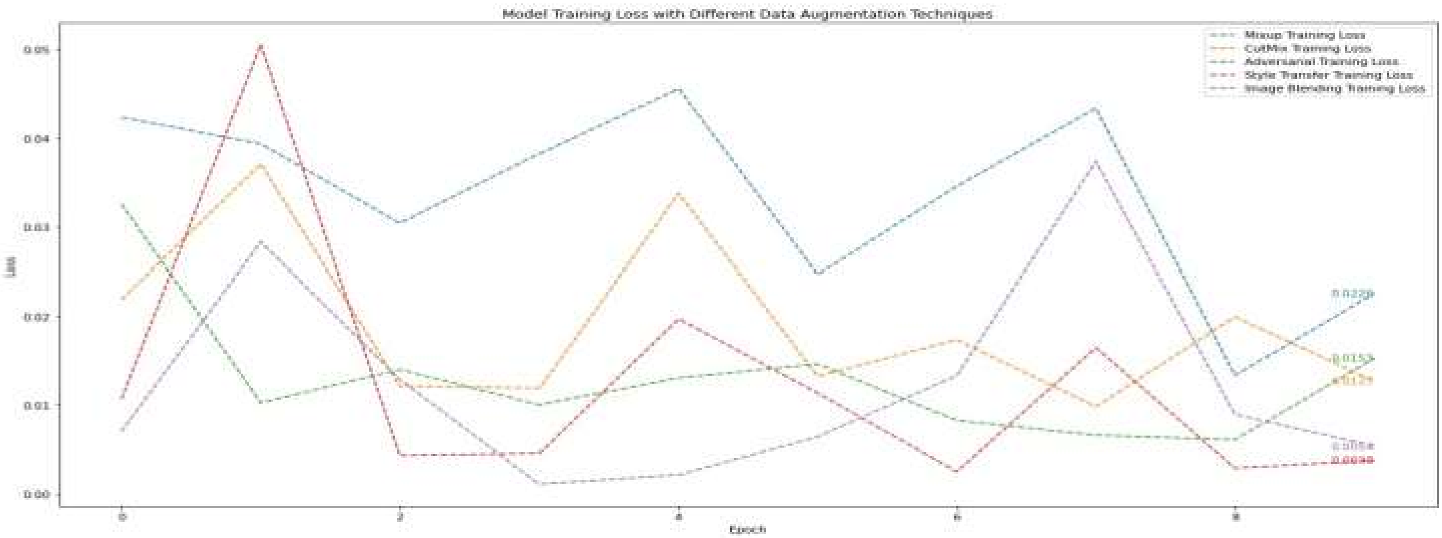


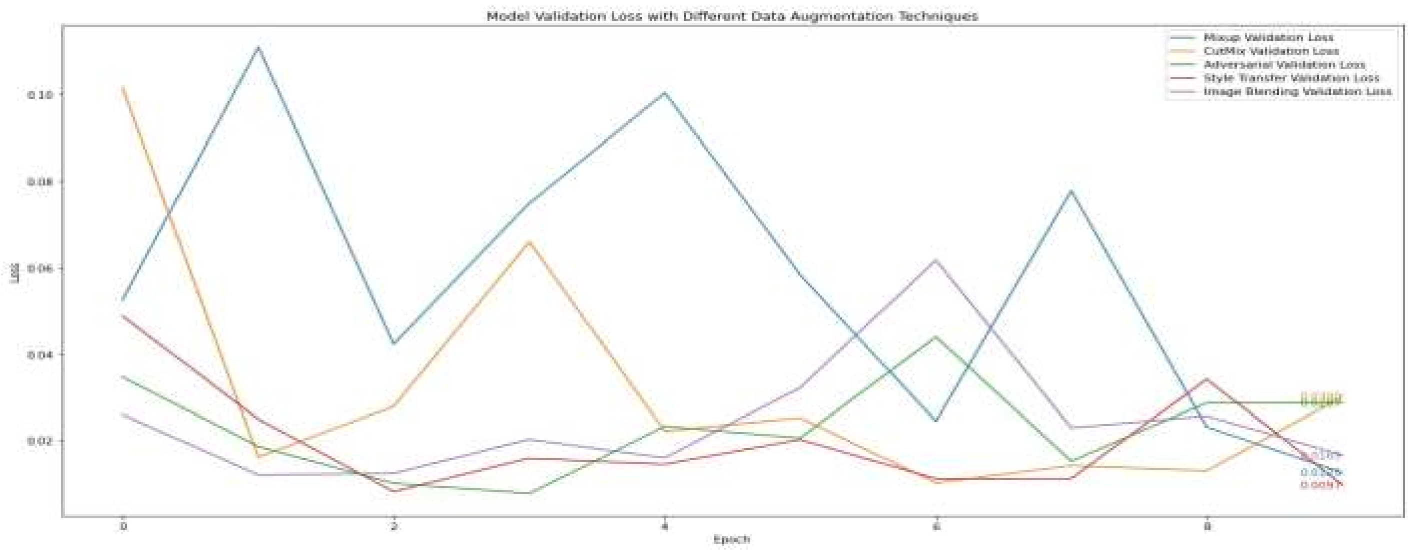
(d)

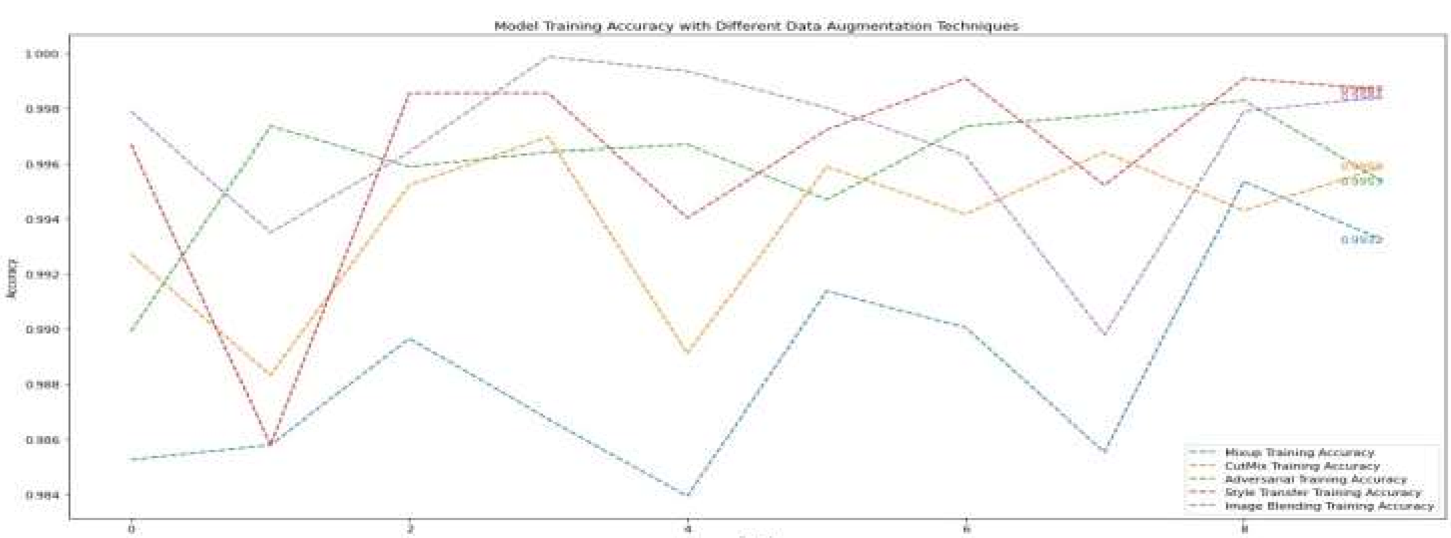


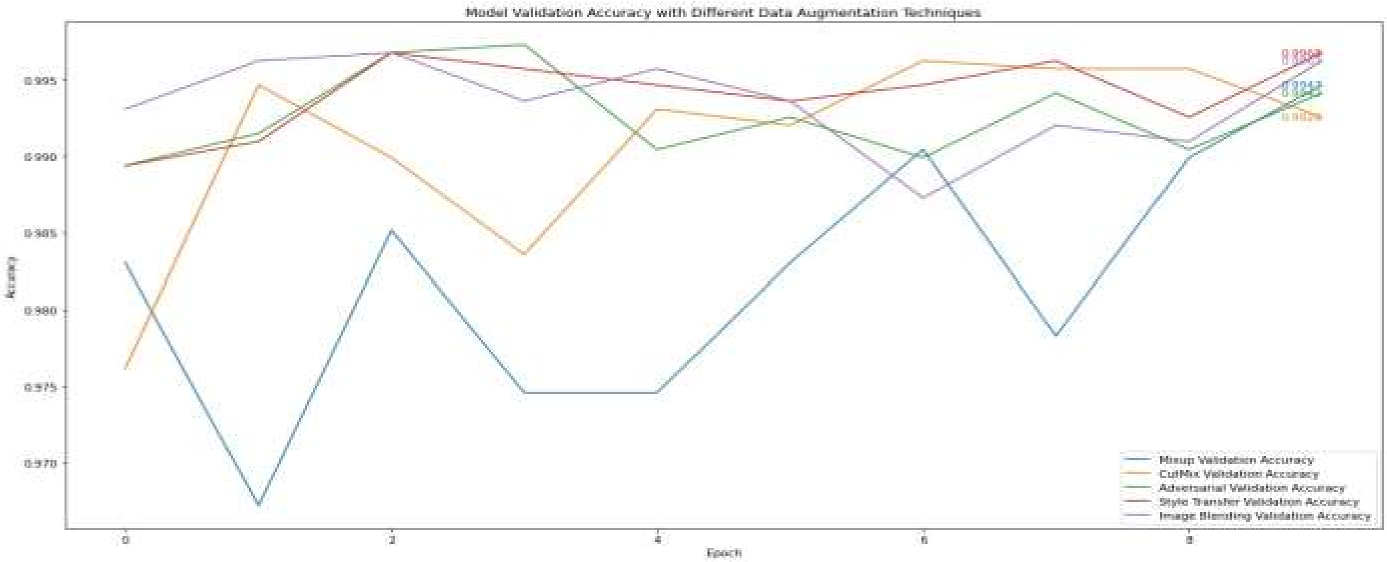
(e)

a) Mixup Data Augmenatation results , b) Cutmix Data Augmenatation results c) Adversarial Data Augmenatation results, d) Image_blending Data Augmenatation results, e) Style_transfer Data Augmenatation results.


Model Training Loss with Different Data Augmentation Techniques
Mixup Training Loss
CutMix Training Loss
Adversarial Training Loss
Style Transfer Training Loss
Image Blending Training Loss
Loss
Epoch


Model Validation Loss with Different Data Augmentation Techniques
Mixup Validation Loss
CutMix Validation Loss
Adversarial Validation Loss
Style Transfer Validation Loss
Image Blending Validation Loss
Loss
Epoch


Model Training Accuracy with Different Data Augmentation Techniques
Mixup Training Accuracy
CutMix Training Accuracy
Adversarial Training Accuracy
Style Transfer Training Accuracy
Image Blending Training Accuracy
Accuracy
Epoch



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