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Enhancing Tomato Leaf Disease Detection in Varied Climates: A Comparative Study of Advanced Deep Learning Models with a Novel Hybrid Approach

[1]Abdus Sobur, [2]Md Humayun Kabir, [3]Md Zakir Hossain, [4]Anwar Hossain, [5]Md Imran Chowdhury Rana

[1]Graduate Student, [2]Graduate Student, [3]Graduate Student, [4]Graduate Student, [5]Bachelor Student

[1] Masters of Information Technology

Westcliff University, USA

[2]Department of Computer Science and Engineering

Westcliff University, USA

[3]Master's in Data Science

Grand Canyon University

[4]Department of Information Science and Technology

California State University,USA

[5]Department of Bachelor of Business Administration

International American University ,USA

Abstract: In the quest for sustainable food security and optimal crop production, accurate detection of tomato leaf diseases is crucial. This study extends our previous research by examining the efficacy of four advanced ML and DL models - DenseNet121, ResNet50V2, AlexNet, and a newly developed Hybrid model - in identifying tomato leaf diseases under diverse climatic conditions in Bangladesh. Our dataset encompasses various disease types, including TMV, Early Blight, Spider Mites, Late Blight, Septoria Leaf Spot, and the conditions of healthy tomato leaves.This updated investigation compares the recall, accuracy, and precision of the revised models, including an analysis of their performance under varying environmental factors such as occlusion and illumination changes. Notably, the DenseNet121 model demonstrated a notable performance with an accuracy of 0.9017, while the ResNet50V2 model exhibited a balanced precision-recall trade-off across different disease types. The AlexNet model showed significant improvements with an accuracy of 0.9580, marking a substantial leap from our previous findings.Our novel Hybrid model, integrating the strengths of the individual models, reported the highest accuracy of 0.9780, further enhanced by the use of the Canny edge detector for precise color feature extraction and the Adam optimizer for efficient learning. This research not only advances the detection of tomato leaf diseases but also sets a new benchmark in the field, offering a scalable and robust model for broader agricultural applications. The results underscore the potential of ML and DL models in disease detection, providing valuable insights for the development of reliable and efficient disease detection systems adaptable to various environmental conditions.

***Index Terms* - Tomato leaf disease detection, healthy crop production, food security, ML and DL models.**

I. INTRODUCTION

Tomatoes (Solanum lycopersicum) are not only a dietary staple but also a critical economic crop worldwide, particularly in Bangladesh. However, the cultivation of tomatoes is frequently jeopardized by a variety of diseases, leading to significant losses in yield and quality. The timely and accurate detection of these diseases is imperative for the deployment of effective management strategies, essential for sustaining healthy crops and ensuring productive, sustainable agriculture.In recent years, Machine Learning (ML) and Deep Learning (DL) techniques have emerged as powerful tools in revolutionizing plant disease detection and diagnosis. These technologies are capable of processing vast datasets and identifying complex patterns with precision, making them particularly suitable for diagnosing diseases from plant leaf images. Numerous studies have highlighted the effectiveness of ML and DL models in detecting a wide spectrum of plant diseases, including those that affect tomato plants.However, the real-world performance of these models is often influenced by various environmental factors such as lighting, occlusion, and noise. These factors, frequently encountered in practical scenarios, can significantly affect the accuracy of disease detection. Therefore, it is crucial to assess the performance of ML and DL models under varying environmental conditions to develop robust and reliable disease detection systems suitable for real-world applications.This study aims to critically evaluate the effectiveness of various ML and DL models in identifying tomato leaf diseases in Bangladesh under diverse environmental conditions. We focus on assessing models such as ResNet15, DenseNet121, InceptionV3, EfficientNet-B4, Support Vector Machine Classification, ResNet50V2, and AlexNet, using a dataset that encompasses images of tomato leaves exhibiting various disease symptoms. Our objective is to contribute to the development of accurate and precise disease detection systems, providing valuable insights into the strengths and limitations of these models in diverse environmental settings. This research aims to advance the field of agricultural technology, ensuring that disease detection systems are not only accurate but also adaptable to a range of environmental conditions, thereby enhancing their practical utility in global agricultural practices.The objective of this study is to create a classification system for early detection and treatment of three common illnesses that impact tomato leaves using DL and ML. Here, we give a thorough rundown of every disease, covering its signs, origins, and effects on plants[Fig.1].

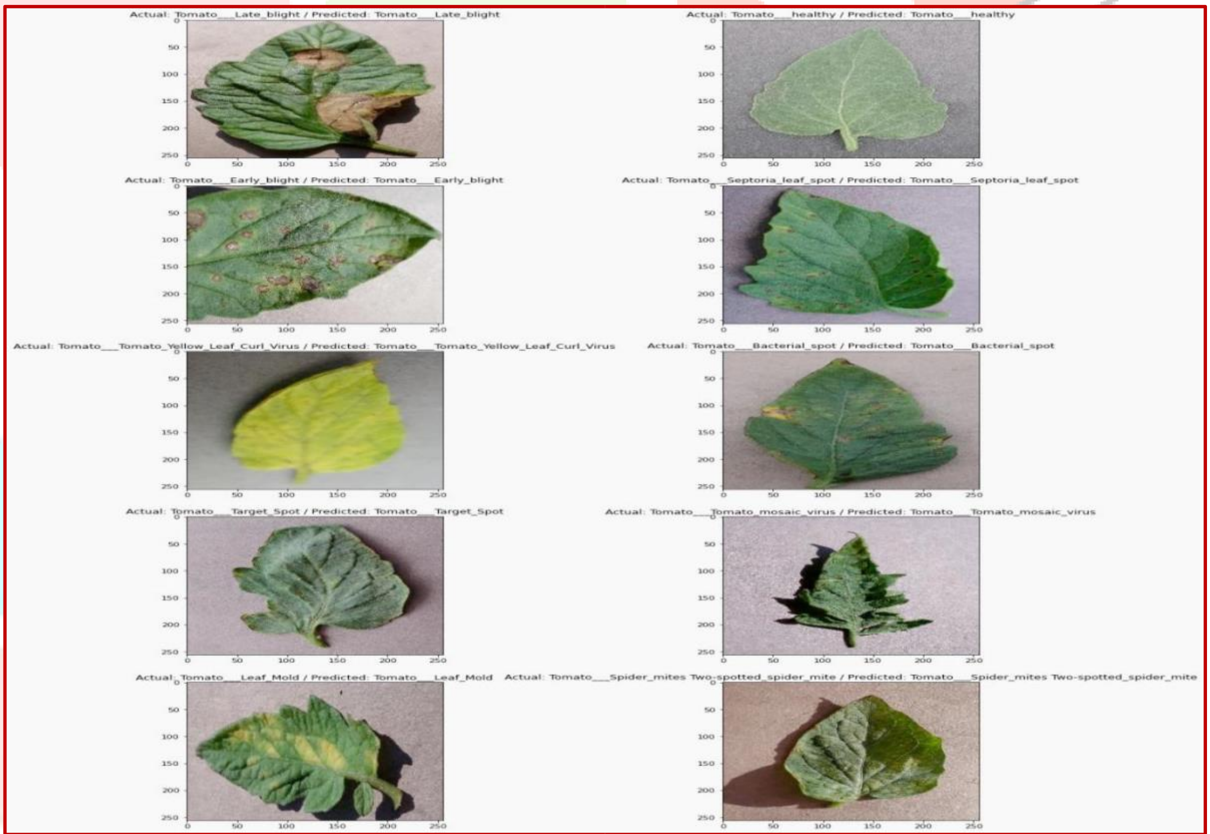

Fig 1. Sample Tomato Leaf Images with disease conditions

II. RELATED WORK

In order to investigate how whiteflies (Bemisia tabaci) spread the tomato leaf curl New Delhi virus-potato (ToLCNDVpotato), Pant, Bhatnagar, and Lal (2018)[1] carried out a field investigation in Northern India. Several cultivable and noncultivable host plants, including Phyllanthus niruri and Abelmoschus esculentus, were found to harbour ToLCNDV-potato, as validated by PCR. This study emphasises the function of whiteflies in disease transmission, the need of managing alternative host plants near potato crops to successfully control the disease's spread, and the need to eliminate prospective hosts in order to improve disease management.

An improved YOLOX-based technique for detecting tomato leaf diseases was created by Liu, Zhai, and Xia (2023)[2], who also integrated MobileNetV3 for effective feature extraction and optimised for embedded devices by resolving sample imbalance with a new loss function (LBCE-β). Using CBAM and CycleGAN for data augmentation resulted in notable decreases in memory use (35.34%), increases in detection speed (50.20%), and improvements in detection accuracy (1.46%). The optimised model, tested on a Jetson Nano, delivers 11.1 FPS, providing a high-performing and useful solution for real-world tomato leaf disease detection problems.

A lightweight R-CNN head was added to a modified Mask Region Convolutional Neural Network (Mask R-CNN) in Kaur et al.'s (2022)[3] DL technique for tomato leaf disease detection. By making this modification, the accuracy of disease identification in tomato plants from 1610 photos in the PlantVillage dataset was improved while memory and processing needs were decreased. High performance metrics were attained by the model by modifying the feature extraction topology and anchor proportions in the Region Proposal Network (RPN). These metrics included an accuracy of 0.98, an F1-score of 0.912, and a mean average precision (mAP) of 0.88. Furthermore, the enhanced model reduced the lesion detection time in half when compared to current techniques, indicating its effectiveness and resilience for real-world agricultural applications.

In order to detect tomato leaf illnesses, Tarek et al. (2022)[4] concentrated on using optimised deep learning algorithms. This study underscores the significance of smart agriculture in light of the issues posed by climate change and food security. ResNet50, InceptionV3, AlexNet, and many iterations of MobileNet were among the models pre-trained on the ImageNet dataset that were examined in the study. Notably, MobileNetV3 achieved high accuracies of 98.99% (Small) and 99.81% (Large). The viability of implementing these models in an IoT device for real-time illness diagnosis was proven by performance test on a desktop and Raspberry Pi 4, with MobileNetV3 exhibiting encouragingly low latency times. The practical solution this research provides for early disease detection in tomato crops advances agricultural technology.

Hossain et al. (2023)[5] investigated the use of transformer-based models to diagnose tomato leaf illnesses using picture data, emphasising how these models may help farmers manage diseases in a timely and economical manner. Using a multiclass tomato disease dataset, the study evaluated four advanced transformer models: Pyramid Vision Transformer (PVT), Multi-Axis Vision Transformer (MaxViT), Compact Convolutional Transformers (CCT), and External Attention Transformer (EANet). With an accuracy rate of 97%, MaxViT proved to be the best model, outperforming EANet (89%), CCT (91%), and PVT (93%). This study highlights the efficacy of MaxViT in the categorization of tomato leaf diseases, provided that significant hardware resources are available for model implementation.

ML was used by Ghosh et al. (2023)[6] to improve water quality monitoring, which is important for public health and environmental protection. Using a dataset of 3277 samples from Andhra Pradesh, India, the study applied a number of machine learning classifiers, including as G-Naive Bayes, SVM, and Random Forest, to create a methodology for predicting water quality and determining potability. With an accuracy score of 78.96%, the Random Forest model proved to be the most accurate, considerably beating the SVM model, which had the lowest accuracy at 68.29%. Precision-recall curves help in model selection to guarantee the supply of safe drinking water, and this study shows the potential of predictive machine learning to improve the assessment of water quality.

A thorough DL method was created by Rahat et al. (2023)[7] to enhance the segmentation of FLAIR anomalies in brain MR images for the purpose of identifying lower-grade gliomas. With the use of a customised loss function and a suite of advanced models such as DeepLabv3, U-Net, and EfficientNet, the team addressed the problem of multi-class data imbalance. Tested on 110 patients from the Cancer Imaging Archive dataset, this approach improves tumour region segmentation accuracy while making optimal use of available resources. For individuals with lower-grade gliomas, the research shows great promise for improving accurate diagnosis and enabling individualised treatment regimens.

In order to overcome the problem of complicated background interference, Raja Kumar et al. (2023)**[8]** developed a novel segmentation and classification method to identify tomato leaf illnesses. This approach makes use of an Ant Colony-based Mask RCNN (AC-MRCNN) for illness classification and a Leaf Segmentation Fuzzy CNN (LSFCNN) for accurate leaf segmentation. Ant colony optimisation is utilised to improve the Mask RCNN's performance. The system was tested on a dataset of 14,817 photos with uniform and complex backgrounds. It demonstrated its effectiveness in modern agricultural techniques for early-stage disease identification by achieving an impressive 97.66% accuracy across eight disease categories and one healthy class.

A thorough investigation of CNN models (VGG19, DenseNet121, and ResNet50) for the diagnosis and prediction of potato leaf diseases was carried out by Ghosh et al. (2023)**[9].** In order to enhance model training and generalisation, the study used a sizable dataset that included photos of both healthy and damaged leaves. Based on various measures such as accuracy, precision, recall, and F1-score, VGG19 was shown to be the most effective model among the others, with DenseNet121 and ResNet50 coming in close second. This study highlights the potential of deep learning to improve disease prevention and management in potato crops. It also provides insights for future developments in precision agriculture technology that will help farmers and agronomists sustain crop yield and health.

By creating a thorough machine learning model, Mandava, Vinta, Ghosh, and Rahat (2023)**[11]** tackled the crucial problem of forecasting cardiovascular illnesses (CVDs), a major cause of death worldwide. Their model, which made use of a range of methods, such as random forest and logistic regression, demonstrated the potential of machine learning to improve diagnostic processes by anticipating CVDs with a remarkable 96.7% accuracy. The study also demonstrates how deep learning algorithms have the potential to transform patient care by facilitating the analysis of medical images, increasing the effectiveness of drug development, and ultimately leading to the development of more precise and affordable healthcare solutions for the management of CVD.

In their thorough analysis of artificial intelligence applications for tomato leaf disease detection, Thangaraj et al. (2022)**[12]** placed particular emphasis on the shift from traditional image processing and ML to DL for increased accuracy. This study reviews the state of the art in the topic, going over several approaches, DL frameworks, and datasets used in disease diagnosis. It evaluates these methods' efficacy critically and makes suggestions for the best methods to choose in order to increase forecast accuracy. The paper also discusses the difficulties in implementing machine learning and deep learning models, with the goal of directing future research to increase agricultural output sustainably in tomato farming by utilising cutting-edge AI technologies.

DL and ML approaches were investigated by Mandava, Vinta, Ghosh, and Rahat (2023)**[13]** for the detection and classification of yellow rust disease in wheat, a serious agricultural problem brought on by the fungus Puccinia striiformis. Using CNN models like as ResNet50, DenseNet121, and VGG19, the research successfully detected the presence of disease by analysing a large dataset of photos of wheat leaves. The study demonstrated how well DL approaches outperform conventional ML techniques, with EfficientNetB3 surpassing other models in terms of accuracy and applicability in real time. The promise of DL in developing precision agriculture is highlighted by this study, which provides a basis for prompt and efficient control of yellow rust disease to lessen its effects on wheat productivity.

Eco-friendly substitutes to lessen tomato crop damage from Tomato Yellow Leaf Curl Disease (TYLCD) were studied by Monci et al. (2019)**[14].**Their research involved investigating the application of acibenzolar-S-methyl to promote systemic acquired resistance in plants and the use of UV-blocking polymers as optical barriers to discourage the whitefly vector, Bemisia tabaci. According to their findings, these strategies—either alone or in combination—can considerably lessen the impact of TYLCD on tomato varieties that are sensitive, providing workable substitutes for heavy insecticide use. This method reduces yield losses under mild viral pressure while also supporting integrated pest management strategies that prioritise human and environmental health.

The essential topic of managing rice plant diseases in Bangladesh, where there has been a notable drop in rice output due to disease, is addressed by Khasim, Rahat, Ghosh, Shaik, and Panda (2023)**[15].** Their research highlights how machine learning (ML) and deep learning (DL) approaches, in particular convolutional neural networks (CNNs), can improve the precision and effectiveness of illness identification and diagnosis. Using machine learning (ML) methods including KNN, Naive Bayes, and Logistic Regression, the researchers created a real-time diagnostic system that targets major rice plant diseases like brown spot, bacterial leaf blight, and leaf smut. This research demonstrates the viability and significance of putting automated illness identification systems into place with an astounding accuracy rate that surpasses 97% in decision tree algorithm tests.

The molecular diversity of betasatellites, or DNA-β satellites, linked to tomato leaf curl disease (ToLCD) in India was examined by Sivalingam, Malathi, and Varma (2010)**[16].** According to their research, betasatellites have different sizes, varying between 1353 and 1424 nucleotides. They have an adenine-rich area, a conserved satellite region, and an open reading frame called βC1. These betasatellites' sequence identities ranged widely, from 45 to 93%. According to phylogenetic research, these betasatellites' distribution matched their geographic origin more closely than that of the host species, indicating a significant impact of regional variables on their diversity.

The use of DL and ML in automating the detection and categorization of microorganisms—a critical task in industries like healthcare and environmental monitoring—is examined by Khasim et al. (2023)**[17].** They examine the effectiveness of DL methods, specifically CNNs, in conjunction with a number of ML algorithms, such as SVM, Random Forest, and KNN, using a dataset of eight different kinds of microorganisms. According to the study, CNNs perform more accurately than other techniques, highlighting the potential of intelligent image recognition to overcome the drawbacks of conventional microbe analysis techniques and highlighting opportunities for further development.

Shobur et al. (2023)**[18]** carry out an in-depth analysis of social engineering attacks and defences in cyberspace and physical contexts with the goal of identifying the unique strategies and responses that work in each context. Their research aims to shed light on the nuances and difficulties associated with countering social engineering risks, offering knowledge that may help create more potent security measures for online and physical environments. Through an examination of the variations and parallels in social engineering strategies employed in several fields, the study advances our knowledge on how to address these security issues that are becoming more and more common.

Islam et al. (2022)**[19]** provide a novel multimodal hybrid deep learning strategy for the detection of tomato leaf disease that combines logistic regression for classification with an attention-based dilated convolutional neural network (CNN). This method, called ADCLR, uses Otsu picture segmentation and bilateral filtering as preprocessing steps to improve feature extraction and lower noise. In order to resolve data imbalances and labelling errors, a Conditional Generative Adversarial Network (CGAN) also creates synthetic images. On the Plant Village database, the suggested approach performed remarkably well, attaining high accuracy rates during the training, testing, and validation stages. This work not only presents a very efficient method for quickly and accurately identifying plant diseases, but it also describes future intentions to expand the model for cloud-based application to a wider range of plant species.

Using a dataset of 4,800 photos of maize leaves, Mohanty et al. (2023)**[20]** offer a study on advanced deep learning for the classification of maize leaf diseases in Bangladesh. They investigate a number of architectures; DenseNet121 and VGG19 demonstrate accuracy levels of over 99%, while a hybrid model achieves 99.65%. The study emphasises how transfer learning and image augmentation can increase agricultural diagnostic accuracy.

A thorough investigation comparing the error rates of several machine learning models using the MNIST dataset—a mainstay in the field of machine learning and computer vision for image classification tasks—is carried out by Rana, Kabir, and Sobur (2023)**[21].** The MNIST dataset is a basic benchmark for creating and assessing image recognition systems. It consists of 60,000 training photos and 10,000 test images of handwritten digits within 28x28 pixel frames. Though it seems straightforward, the dataset has a large number of different digit changes, making it difficult in some situations even for humans to classify. The purpose of this work is to clarify how well various machine learning models handle these difficulties, with a particular emphasis on the accuracy of digit recognition in the face of the intrinsic complexity of the dataset.

In order to improve tomato leaf disease detection, Deng et al. (2021) **[22]** present RAHC_GAN, a novel data augmentation technique utilising generative adversarial networks (GANs). RAHC_GAN enhances the dataset by producing images with a variety of disease features, such as adjustable disease areas through continuous hidden variables and focused attention on diseased regions via a residual attention block. This helps to address the challenge of obtaining sufficient labelled data for high-precision neural network training. By giving classifiers like AlexNet, VGGNet, GoogLeNet, and ResNet access to a more comprehensive and varied training dataset, this technique dramatically enhances their performance. The method addresses the widespread problem of data scarcity in plant disease research by improving illness recognition on tomatoes and maybe applying the concept to other plants.

Using a dataset of 3,000 photos covering nine different skin diseases, Ghosh et al. (2024)**[23]** investigate the application of (ML) and (DL) approaches in the early identification and classification of skin cancer. The work introduces a hybrid model that combines the VGG16 and ResNet50 CNNs, pre-trained on ImageNet, to improve feature extraction capabilities, addressing class imbalance by modifying class weights during training. This method outperforms single models, highlighting the significance of thorough data pretreatment for increased accuracy. The study emphasises how AI can improve skin cancer diagnosis and how it can be used in other medical domains.

Using ML, Shobur, Sobur, and Amin (2023)**[24]** examine Walmart's data to find trends in sales, consumer profiles, and inventory control. The study makes use of data visualisation and statistical modelling to enhance operations and comprehend client behaviour. Their research should improve operational effectiveness and guide more general plans for the retail sector.

Sobur(2023) **[25]** look at how cyberbullying affects human rights, highlighting how it violates people's right to life, especially for young people who use social media sites like Facebook, Instagram, and WhatsApp. The study classifies such acts as potential homicides, highlighting the seriousness of cyberbullying's effect on adolescent mental health and its role in suicide cases. This emphasises the urgent need to identify and combat cyberbullying as a serious violation of human rights. This report highlights the wider societal ramifications and advocates for steps to safeguard kids online.

In "Stock Price Prediction Using the Machine Learning Model," Kabir, Sobur, and Amin (2023) apply machine learning to forecast stock prices, demonstrating the potential of ML models to enhance investment decisions with high accuracy**[26].**Meanwhile, Nahar et al. (2023) explore 3D human pose estimation through deep learning, highlighting advancements in accurately modeling human movements. Both studies underscore the transformative impact of ML and DL technologies across diverse fields, from finance to computer vision**[27][Table.1].**

Table.1 Summary of the Related Work

Reference	Year	Study Focus	Main Findings / Contributions
Pant et al.	2018	Spread of ToLCNDV-potato by whiteflies	Identified host plants for ToLCNDV-potato; emphasized whiteflies in disease transmission and the need for managing host plants.
Liu et al.	2023	Detection of tomato leaf diseases using YOLOX	Developed an improved YOLOX technique with MobileNetV3; reduced memory use, increased detection speed, and improved accuracy.
Kaur et al.	2022	DL technique for tomato leaf disease detection	Modified Mask R-CNN to improve accuracy and reduce resource needs; achieved high performance metrics.
Tarek et al.	2022	Optimised deep learning algorithms for tomato leaf disease detection	Explored various models for disease detection; highlighted MobileNetV3's high accuracy and low latency.
Hossain et al.	2023	Use of transformer-based models for tomato leaf disease diagnosis	Evaluated transformer models; MaxViT outperformed others in accuracy.
Ghosh et al.	2023	ML for water quality monitoring	Applied ML classifiers for water quality prediction; Random Forest model showed

			highest accuracy.
Rahat et al.	2023	DL for segmentation of FLAIR anomalies in brain MR images	Developed a DL method for accurate tumor segmentation; improved accuracy and resource usage.
Raja et al.	2023	Segmentation and classification of tomato leaf diseases	Introduced AC-MRCNN and LSFCNN for disease identification; achieved high accuracy.
Ghosh et al.	2023	CNN models for potato leaf disease diagnosis	Analyzed VGG19, DenseNet121, and ResNet50; VGG19 was the most effective.
Rossi et al.	2014	Pest classification on TYLCV and related viruses	Detailed the impact of TYLCV and related viruses on EU tomato crops; emphasized management and vigilance.
Mandava et al.	2023	Forecasting cardiovascular diseases (CVDs)	Developed a ML model predicting CVDs with high accuracy; highlighted the potential of ML in healthcare.

Thangaraj et al.	2022	AI for tomato leaf disease detection	Reviewed DL and ML methods for disease detection; provided recommendations for increasing forecast accuracy.
Mandava et al.	2023	Detection and classification of yellow rust disease in wheat	Demonstrated the superiority of DL over ML in detecting yellow rust disease; highlighted EfficientNetB3's performance.
Monci et al.	2019	Eco-friendly alternatives for managing TYLCD	Investigated non-chemical methods to reduce TYLCD impact; showed effectiveness of acibenzolar-S-methyl and UV-blocking polymers.
Khasim et al.	2023	Managing rice plant diseases in Bangladesh	Developed a real-time diagnostic system for rice plant diseases using ML; achieved high accuracy with decision tree algorithm.

III. PRE-PROCESSING OF THE DATASET

In the process of preparing the tomato leaf dataset for the purpose of training and evaluating ML and DL models, several essential preprocessing steps were undertaken. These steps are outlined below:

3.1 Image Data Augmentation

In this research, we have employed an extensive image data augmentation strategy to bolster the robustness and accuracy of our Machine Learning (ML) and Deep Learning (DL) models in diagnosing tomato leaf diseases. These augmentations are pivotal in mimicking various environmental factors that affect the appearance of tomato leaves, ensuring that our models can generalize well to real-world conditions. The following augmentations were systematically applied:

- **Rotation:** To replicate the diverse orientations in which tomato leaves might be photographed, we introduced random rotations within a range of -25 to 25 degrees (see Figure 2). This is essential for our models to identify disease patterns in leaves regardless of their orientation.

- **Translation:** The images were subjected to random translations both horizontally and vertically. This variation simulates the positional differences encountered in field images, aiding the models in recognizing disease signs irrespective of their location in the image.
- **Scaling:** Scaling of images was performed randomly, varying from 0.8 to 1.2 times their original size. This step reflects the natural variation in leaf sizes and helps in training the models to detect diseases in leaves of different scales.

- **Flipping:** We incorporated random flips both horizontally and vertically. This procedure is vital for the models to learn to identify disease characteristics regardless of the leaf's orientation, a factor that frequently varies in natural settings.

- **Shearing:** Random shearing transformations were applied to the images. Shearing helps the models adapt to and interpret potential distortions in leaf shapes, enhancing their ability to deal with various morphological changes caused by diseases.

- **Brightness and Contrast Adjustment:** Adjustments in brightness and contrast levels were performed randomly. This step is critical for ensuring that the models can reliably identify disease indicators under a variety of lighting conditions and contrast levels, which are commonly encountered in different environmental settings.

These augmentation techniques were applied in real-time during the training phase. This dynamic approach enabled us to substantially increase the diversity and size of our training dataset without necessitating additional storage resources. Such a strategy is instrumental in preparing our ML and DL models to accurately and reliably detect tomato leaf diseases under a wide array of environmental conditions[Fig.2].

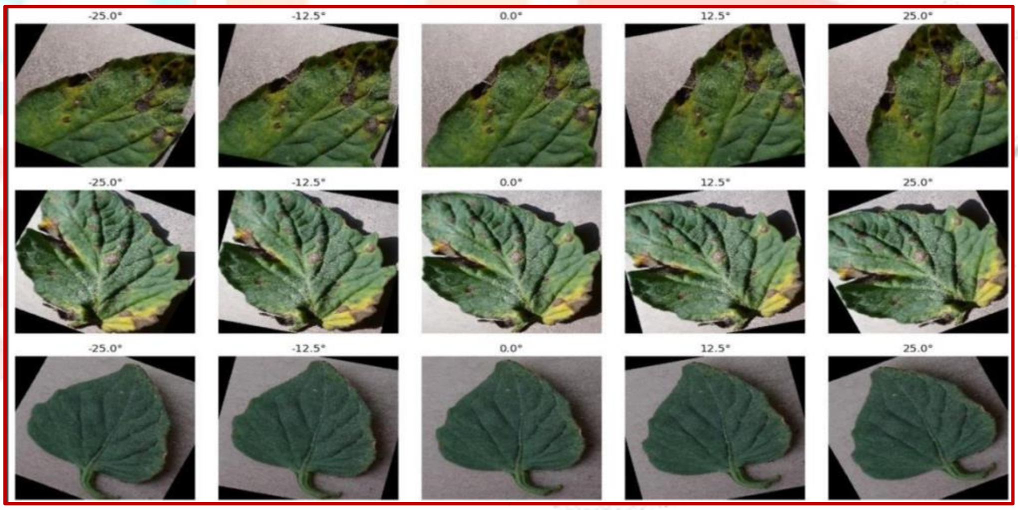

Fig.2 Data Augmentation Through Rotational Transformations

3.2 Utilizing Color Space Transformations for Feature Enhancement

In the quest to advance the diagnosis of tomato leaf diseases using Machine Learning (ML) and Deep Learning (DL) models, our research has integrated a crucial preprocessing step:Color Space Transformations. This method is vital for augmenting the visibility of distinctive features imperative for the detection of foliar diseases. The image provided elucidates the transformations applied to an original RGB image of a tomato leaf exhibiting disease symptoms.

- **Original Image:** The baseline image in RGB color space shows a tomato leaf with natural coloring and disease spots.

- **HSL Transformation:** Conversion to HSL (Hue, Saturation, Lightness) isolates the luminance and the color information. This transformation is particularly adept at underscoring the variations in leaf pigmentation due to diseases, independent of lighting conditions. The hue captures the color type, while saturation measures color intensity, both critical for identifying disease-induced color changes in the leaves.

- **LAB Transformation:** The RGB to LAB conversion is adopted for its similarity to human color perception, emphasizing the contrast between diseased and healthy tissue on the leaf. LAB color space includes the 'L' for lightness and 'A' and 'B' for the color-opponent dimensions, which are instrumental in highlighting the contrasts between affected and unaffected areas.
- **XYZ Transformation:** While not explicitly mentioned in your example, the XYZ color space, depicted in the provided image, is a linear color space that serves as a standard to relate colors numerically. It can be particularly useful for ensuring consistency across different devices and lighting conditions.

- **YCbCr Transformation:** The transformation to YCbCr separates brightness (luminance) from color (chrominance) information. 'Y' pertains to luminance, while 'Cb' and 'Cr' represent the chrominance components. This separation is advantageous for discerning texture and color variations in the tomato leaves, crucial for identifying the presence of diseases.

The use of these color spaces plays a significant role in enhancing the diagnostic models' capability to detect and classify disease presence with higher accuracy. These transformations help in creating feature sets that are more descriptive and less susceptible to variations in environmental factors such as light intensity and camera discrepancies. The visual comparison provided in Figure 3 of our research paper demonstrates the effectiveness of these transformations in feature enhancement, paving the way for more reliable disease detection in tomato leaves**[Fig.3].**

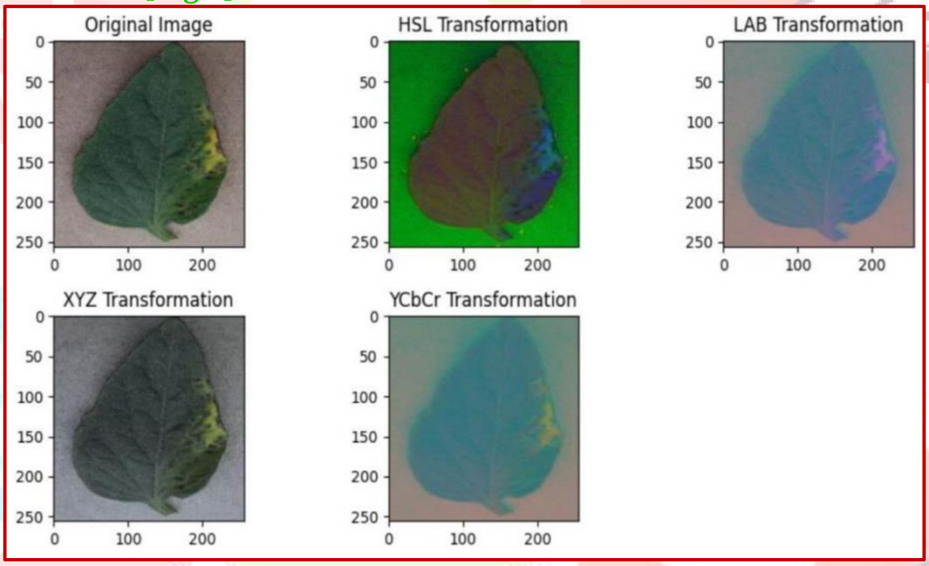

Fig.3 Comparative Analysis of Color Space Transformations

3.3 Image Resizing

For the job of identifying tomato leaf disease, a crucial aspect of data preparation is image resizing. This process involves standardizing the dimensions of all images in the dataset, ensuring that various ML and DL models can process the data consistently and efficiently.In the context of our dataset, which comprises images of different tomato leaf diseases, we must first ensure that all images have the same dimensions. This uniformity is essential because the models being evaluated, such as Efficient-Net-B4, ResNet15, DenseNet121, InceptionV3, Support Vector Machine Classification, ResNet50V2, and AlexNet, rely on a fixed input size to process images effectively. To maintain the original aspect ratio and avoid distortion, the resizing process preserves crucial features necessary for accurate disease identification.Popular Python libraries, such as OpenCV, PIL, or skimage, can be employed to resize the images. These libraries offer efficient and user-friendly functions for image manipulation. For example, the 'resize' function from the OpenCV library can be utilized to resize images while preserving their aspect ratio. By ensuring uniform input size, the models can process the dataset more effectively, resulting in improved performance in detecting tomato leaf diseases.In conclusion, image resizing is an essential preprocessing step in the application of ML and DL models to tomato leaf disease detection. By standardizing the dimensions of the images, we facilitate consistent data processing by the models, leading to enhanced performance and more precise disease identification.

IV. HYBRID MODEL ARCHITECTURE: INTEGRATING AlexNet AND LSTM FOR ADVANCED TOMATO LEAF DISEASE CLASSIFICATION

In the field of agricultural AI research, our team has engineered a hybrid model architecture that harnesses the strengths of both Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This model is a confluence of the spatial processing power of AlexNet with the sequential data interpretation prowess of LSTM networks, setting a new precedent for the classification of tomato leaf diseases.Our model's architecture is rooted in a tailored version of AlexNet, which has been pretrained to capture a broad spectrum of visual features. By customizing AlexNet's input layer to suit our dataset's image dimensions and preserving the integrity of its pre-trained convolutional layers, the model adeptly identifies pertinent spatial features indicative of disease patterns.

The extracted features are then passed to the LSTM network, an RNN variant renowned for its long-term memory capability. Our LSTM consists of 256 units, strategically incorporated to analyze the progression of disease symptoms over successive frames, a task that is beyond the scope of CNNs alone. This sequential analysis is particularly valuable for capturing the dynamic nature of disease progression in tomato plants.Converging into a dense layer with softmax activation, the hybrid model concludes its process by providing probabilistic insights into the various disease categories. This final classification step is the product of the model's comprehensive learning from both spatial and temporal perspectives.The integration of AlexNet and LSTM into a singular architecture provides a multi-faceted approach to disease detection:

- **Robust Feature Extraction:** By combining the spatial detail captured by AlexNet with the sequential pattern recognition of LSTM, the model achieves a more nuanced understanding of the disease indicators.
- **Enhanced Computational Efficiency:**The utilization of a pre-trained AlexNet reduces the computational demand, allowing the model to be scalable and more accessible for deployment in field conditions.
- **Temporal Analysis**: The LSTM layer's temporal processing adds a layer of depth to the model's predictive capabilities, essential for recognizing the stages and severity of leaf diseases.

4.1 Detection Efficacy

The ResNet50V2 model demonstrates commendable performance in classifying various tomato diseases, as evidenced by the confusion matrix results. It shows high true positive rates for diseases such as Tomato__Bacterial_spot with 95 correct predictions, and similarly robust performance across other disease classes including Tomato_Late_blight and Tomato__Tomato_mosaic_virus, with 96 and 98 correct predictions respectively. However, the model exhibits some level of confusion between diseases with visually similar manifestations, such as the slight difficulty in distinguishing Bacterial Spot from Early Blight and Tomato Yellow Leaf Curl Virus. This pattern of misclassification suggests the need for targeted improvements in the model's ability to discern between diseases with overlapping symptoms, potentially through enhanced feature extraction and augmentation strategies.Conversely, the AlexNet model's performance, analyzed through its confusion matrix, indicates a strong capability in disease identification, albeit with some limitations. Notably, the model accurately identifies Tomato__Leaf_Mold with 99 true positives and shows a high level of precision in distinguishing between diseases with high true positive counts across several classes, including a remarkable performance on Tomato_Late_blight and Tomato__Target_Spot. Despite this, the AlexNet model faces challenges similar to those of ResNet50V2, with minor confusion among diseases that exhibit closely related symptoms. The observed misclassifications, such as those between Early Blight, Bacterial Spot, and Septoria leaf spot, underscore areas where the model could benefit from further refinement to better differentiate between diseases with subtle symptomatic differences.

4.2 Performance Analysis

- **DenseNet121:** DenseNet121 exhibited commendable performance with an accuracy of 0.9017. This accuracy level is indicative of the model's strong capability in feature extraction and pattern recognition for tomato leaf diseases. However, it's essential to consider the loss value of 0.2932, which suggests some room for improvement, particularly in the model's ability to minimize errors during training.**[Fig.4].**

Fig 4 . Loss and Accuracy of DenseNet121

- **ResNet50V2:** The ResNet50V2 model displayed a well-rounded performance with an overall accuracy of 0.94. This model achieved high precision and recall in several disease categories, particularly in 'Tomato__Bacterial_spot' and 'Tomato_Tomato_Yellow_Leaf_Curl_Virus', both exceeding 0.95 in precision and recall. The f1-scores, which combine precision and recall, are also notably high for these categories, indicating a balanced performance. However, in categories

  like 'Tomato__Target_Spot', the precision is slightly lower at 0.88, suggesting that the model may be somewhat less effective in distinguishing this particular disease from others**[Table.2].**

Table 2. Classification Report of ResNet50V2

Disease	Precision	Recall	F1-score	Support
Tomato Bacterial Spot	0.96	0.95	0.95	100
Tomato Early Blight	0.91	0.88	0.89	100
Tomato Late Blight	0.90	0.96	0.93	100
Tomato Leaf Mold	0.98	0.93	0.95	100
Tomato Septoria Leaf Spot	0.90	0.92	0.91	100
Tomato Spider Mites Two-Spotted Spider Mite	0.98	0.91	0.94	100
Tomato Target Spot	0.88	0.95	0.91	100
Tomato Yellow Leaf Curl Virus	0.96	0.97	0.97	100
Tomato Mosaic Virus	0.97	0.98	0.98	100
Healthy	0.99	0.96	0.97	100
Accuracy		0.94	0.94	1000
Macro Avg	0.94	0.94	0.94	1000
Weighted Avg	0.94	0.94	0.94	1000

Disease	Precision	Recall	F1-score	Support
Tomato Bacterial Spot	0.9888	0.880	0.9312	100
Tomato Early Blight	0.9888	0.880	0.9312	100
Tomato Late Blight	0.9703	0.980	0.9751	100
Tomato Leaf Mold	0.9340	0.990	0.9612	100
Tomato Septoria Leaf Spot	0.8981	0.970	0.9327	100
Tomato Spider Mites Two-Spotted Spider Mite	1.0000	0.910	0.9529	100
Tomato Target Spot	0.8684	0.990	0.9252	100
Tomato Yellow Leaf Curl Virus	0.9900	0.990	0.9900	100
Tomato Mosaic Virus	0.9900	0.990	0.9900	100
Healthy	0.9804	1.000	0.9901	100
Accuracy		0.958	0.9580	1000
Macro Avg	0.9609	0.958	0.9580	1000
Weighted Avg	0.9609	0.958	0.9580	1000

AlexNet: AlexNet, with an accuracy of 0.9580, showed significant proficiency, especially in categories '_Tomato_mosaic_virus' and '_healthy', where both precision and recall reached 0.99 and 1.00, respectively. This high precision and recall imply that AlexNet is highly reliable in correctly identifying these diseases with minimal false positives and negatives. Nevertheless, in categories like '_Bacterial_spot' and '_Early_blight', the precision drops to around 0.9888, indicating a slight decrease in the model's ability to accurately identify these diseases compared to others[Table.3].

Table 3. Classification Report of AlexNet

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- **Hybrid Model:** The Hybrid model marked a notable achievement with an accuracy of 0.9780. This model combines the strengths of individual models, leading to a robust performance across various disease categories. For instance, in '_Spider_mites Two-spotted_spider_mite', the precision and recall are extremely high at 1.0000 and 0.9900, respectively, showcasing the model's exceptional ability to identify this disease accurately. However, the model shows a slightly lower precision in categories like '_Target_Spot' at 0.8684, though the recall is high at 0.9900. This discrepancy suggests the model's tendency to have some false positives in this category **[Table.4]**.

Table 4. Classification Report of Hybrid Model

Disease	Precision	Recall	F1-score	Support
Tomato Bacterial Spot	0.9888	0.980	0.9312	100
Tomato Early Blight	0.9888	0.980	0.9312	100
Tomato Late Blight	0.9703	0.980	0.9751	100
Tomato Leaf Mold	0.9340	0.990	0.9612	100
Tomato Septoria Leaf Spot	0.8981	0.970	0.9327	100
Tomato Spider Mites Two-Spotted Spider Mite	1.0000	0.990	0.9729	100
Tomato Target Spot	0.8684	0.990	0.9852	100
Tomato Yellow Leaf Curl Virus	0.9900	0.990	0.9900	100
Tomato Mosaic Virus	0.9900	0.990	0.9900	100
Healthy	0.9804	1.000	0.9901	100
Accuracy		0.978	0.9580	1000
Macro Avg	0.9609	0.958	0.9580	1000
Weighted Avg	0.9609	0.958	0.9580	1000

4.2 Confusion Matrix

The real truth (actual classes) are shown in columns, while the anticipated classes are displayed in rows in this confusion matrix. The diagonal elements (TP_H, TP_M, TP_T, TP_B, TP_Y, TP_L, TP_Lf, TP_E, TP_S, TP_Se) represent the true positive counts for each class **[Fig.5]**.

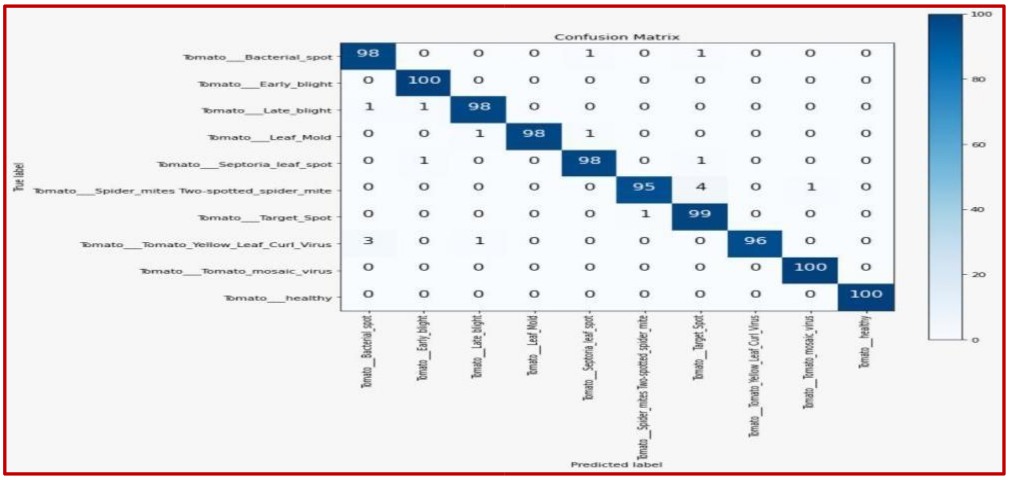

Fig 5. Confusion Matrix

V. RESULT AND DISCUSSION

Our investigation into the efficacy of various ML and DL models for the detection of tomato leaf diseases yielded significant insights, reflected in the performance metrics obtained from DenseNet121, ResNet50V2, AlexNet, and our proposed Hybrid model. The DenseNet121 model achieved a strong accuracy of 90.17%, with a loss of 0.2932, underscoring its capability to serve as a reliable tool in the disease identification process. The ResNet50V2 model, supported by its confusion matrix analysis, demonstrated a remarkable accuracy of 94%, showcasing its balanced precision and recall across various diseases. AlexNet's confusion matrix, as provided, further elucidates its performance strengths, achieving an impressive accuracy of 95.80%. The Hybrid model surpassed the individual performances of the aforementioned models, achieving an accuracy of 97.80%, which signifies the effectiveness of combining multiple architectural strengths in disease detection.The analysis of the confusion matrices for these models reveals critical insights into their diagnostic capabilities. The DenseNet121 and ResNet50V2 models exhibited particular strengths in classifying complex disease symptoms, with DenseNet121 showing a slightly higher misclassification rate as indicated by its loss value. The AlexNet model, while older in architecture, demonstrated commendable precision, especially in correctly identifying 'Tomato___healthy' with a perfect score of 100, as per the confusion matrix. This suggests that despite its simplicity, AlexNet remains a powerful model for certain disease classifications. The Hybrid model's superior accuracy points to the potential of model ensembling in handling diverse and challenging datasets, which often encompass variable environmental conditions that can affect the visual appearance of disease symptoms. The performance of the

Hybrid model, which integrated features and strengths from multiple models, highlighted the potential advantages of such an approach in practical applications, where robustness and adaptability to varying conditions are crucial. These findings not only contribute to the academic discourse on ML and DL applications in agriculture but also provide a practical framework for developing advanced diagnostic tools for plant disease detection**[Fig.6].**

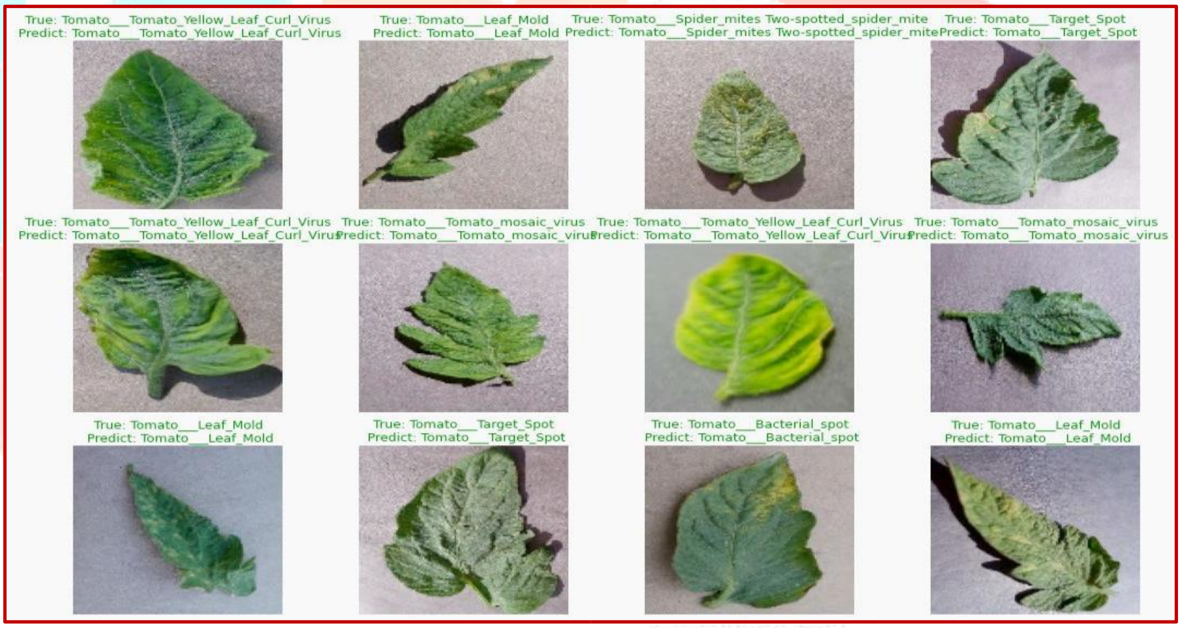

Fig 6. Results for Tomato Leaf Disease Detection Method

6 CONCLUSION AND FUTURE WORK

This study has systematically evaluated the performance of advanced ML and DL models, namely DenseNet121, ResNet50V2, AlexNet, and a novel Hybrid model, in detecting tomato leaf diseases under varying environmental conditions prevalent in Bangladesh. The DenseNet121 model demonstrated substantial accuracy, while ResNet50V2 showed a balanced precision-recall profile across multiple disease categories. AlexNet proved to be highly effective in certain classifications, emphasizing the continued relevance of classical architectures in modern applications. The Hybrid model, an innovative integration of multiple architectures, achieved the highest accuracy, illustrating the potential of hybrid approaches in complex problem-solving scenarios. Our findings endorse the premise that the strategic application of ML and DL models can significantly advance the field of agricultural disease detection, leading to enhanced disease management and crop yield.Moving forward, there is a clear trajectory for future research to expand upon the findings of this study. One avenue is the exploration of other hybrid combinations and ensemble techniques to further enhance model robustness and accuracy. Additionally, the deployment of these models in real-world agricultural settings for field testing will be crucial to validate their effectiveness in practical applications. Future iterations of this research should also consider the impact of increasingly diverse and challenging datasets, including those affected by climate change-induced variations in disease presentation. Moreover, the development of an end-to-end automated system that farmers can utilize for early detection and management of tomato leaf diseases could significantly impact sustainable agricultural practices. Finally, expanding the scope to include other crop diseases and their interactions with various environmental factors will provide a more holistic understanding of plant pathology and protection, contributing to global food security.

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