EfficientNet-Based Deep Learning Approach for Accurate Tomato Leaf Disease Detection

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Abstract

This research paper presents a comprehensive solution for the accurate detection of tomato plant diseases using deep learning techniques. The primary objective is to develop a real-time model capable of accurately identifying a broad spectrum of diseases present on tomato leaves thereby allowing for opportune interventions to mitigate extensive crop losses. Utilizing the capabilities of the EfficientNet-B1 architecture this method enables the classification of fifteen distinct disease categories including healthy leaves. Utilizing the publicly accessible PlantVillage dataset in conjunction with diligent data preprocessing ensures robust training and validation of the model. Using a meticulous five-fold cross-validation strategy the performance of the model is thoroughly evaluated. Precision, recall, F1-score and accuracy metrics consistently exceed 98% and in some cases, exceed 99%. This extraordinary precision surpasses previous research efforts and demonstrates the efficacy of the proposed methodology. Deep learning this methodology greatly improves disease management efficacy, ensuring healthier crop yields also increased food security and sustainable agricultural practices. However, the prospective application of the developed model in the real world has the potential to revolutionize precision agriculture and the field of plant disease detection. The systematic approach meticulous evaluation and exceptional precision of the paper all contribute to its significant impact in the field.

Keywords: ***Tomato diseases, Deep learning, Transfer learning, EfficientNet-B1.***

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1. INTRODUCTION

Tomato cultivation is a vital pillar of global agriculture, providing food and economic support to communities around the globe. To ensure the robustness and productivity of tomato crops, the interplay between agricultural innovation and sustainable practices is essential. in this context, the objective of this in-depth study is to develop a methodological framework that provides a robust and effective solution for the accurate identification and classification of diseases affecting tomato plants.

The inherent connection between thriving tomato crops and food security emphasizes the importance of disease management in agriculture. As tomato crops are threatened by a variety of pathogens, early detection and accurate classification are essential to limit crop losses and ensure food security.

The overarching objective of this investigation is to contribute to the comprehension of tomato plant disease detection and classification by employing innovative technological insights. By combining the fields of agriculture and technology, this study aims to equip farmers with an easily accessible instrument that improves their capacity to diagnose and treat a broad spectrum of plant diseases.

This extensive study's main objective is to develop a robust and effective methodology for the precise identification and meticulous classification of tomato plant diseases. The proposed method is meticulously crafted to serve as a practical and accessible instrument, equipping farmers with the means to diagnose and effectively manage an array of plant diseases. This endeavor aims to enhance the overall resilience and productivity of tomato crops by integrating advanced technological insights into agricultural practices, thereby nurturing a sustainable and bountiful agricultural ecosystem.

Answering important research questions that support its objectives:

How can advanced deep learning techniques be utilized to accurately detect and classify tomato plant diseases?

What effect does early disease detection have on the overall health and yield of tomato crops?

How can the integration of technological advances and agricultural practices contribute to the development of tomatoes that are resilient and sustainable?

This study highlights the intersection of technology and agriculture by outlining a methodological framework that aims to improve the resilience, productivity, and sustainability of tomato cultivation. This research seeks to contribute significantly to the field of plant disease management by incorporating cutting-edge techniques, thereby fostering a more prosperous agricultural future.

LITERATURE REVIEW

Precision farming has emerged as a promising approach to mitigate the challenges posed by plant diseases and pests in agriculture. This strategy leverages advanced technologies like sensor networks, remote sensing, and robots to enable targeted interventions. By reducing reliance on costly chemicals and interventions, precision farming offers a sustainable solution. Accurate disease detection is pivotal for effective targeted treatments, often facilitated by technologies such as drones, robots, and sensor networks. However, these technological tools lack the expertise of human observers, necessitating data processing techniques that mimic expert knowledge.

Deep learning techniques have revolutionized image processing in disease detection. Mohanty et al. \cite{mohanty2016using} employed artificial neural networks with hidden layers to successfully identify and classify various plant diseases. The shift from traditional methods to deep learning has transformed classification tasks. Clustering and decision-making procedures have also been incorporated into disease detection and categorization.

Deep learning techniques like Convolutional Neural Networks (ConvNets) and Residual Networks (ResNet) have demonstrated exceptional efficacy in accurate disease detection. The integration of hyperspectral data with feature-based approaches, as seen in \cite{ashourloo2016investigation} \cite{parikh2016disease} and \cite{sabrol2016tomato}, has significantly improved disease detection.

Notable studies have explored different deep learning architectures for disease classification. Mohanty et al. \cite{mohanty2016using} employed the AlexNet architecture \cite{krizhevsky2012imagenet} to classify plant diseases, achieving success even with previously unseen illnesses. Rangarajan et al. \cite{rangarajan2018tomato} fine-tuned models like AlexNet and VGG16net, adjusting parameters such as batch size and learning rates. Integration of convolution and pooling layers into the Inception V4 architecture \cite{szegedy2017inception} yielded dimension reduction benefits. Too et al. \cite{too2018comparative} incorporated ImageNet weights into their architecture, fine-tuning DenseNets \cite{huang2017densely} for plant disease recognition.

This study introduces the utilization of the EfficientNet architecture \cite{tan2019efficientnet} for plant disease classification. To evaluate performance, a comparison is drawn against state-of-the-art CNN architectures, including AlexNet, ResNet, DenseNet, SqueezeNet and Decision Tree 3. Through this exploration, the study contributes to the growing body of research in deep learning-based plant disease detection, shedding light on the potential of advanced technologies for revolutionizing agricultural practices.

2. PROPOSED METHOD

This section of the study describes the data collection procedure, the data preprocessing stages the development of EfficientNet-B1 and the matrices used to evaluate the classification performance of the proposed architecture. Figure 1 illustrates the comprehensive technique utilized for this research undertaking.

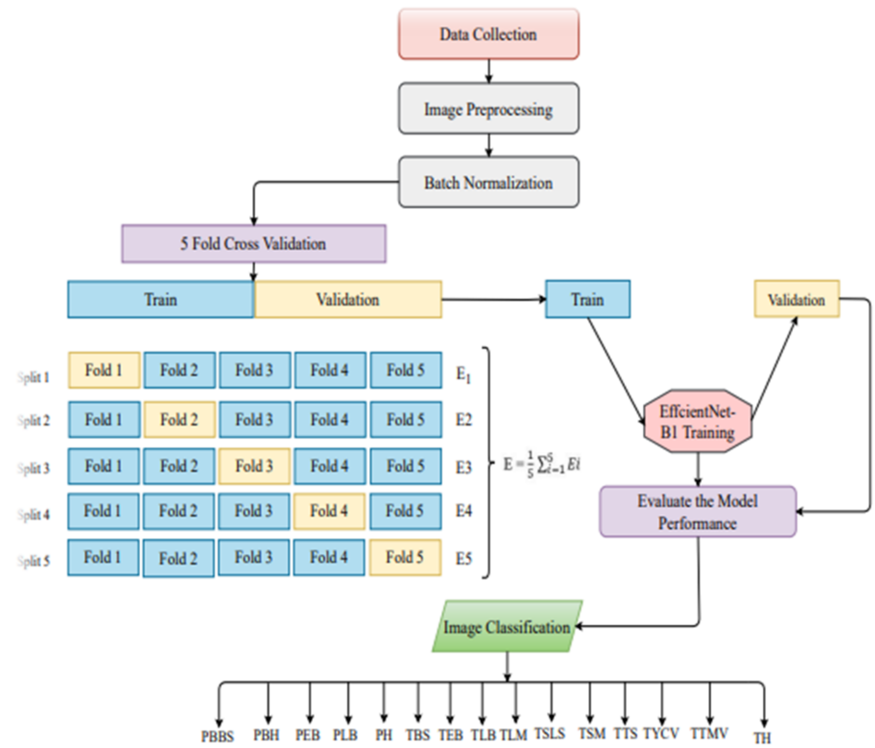

Fig. 1: Proposed methodology

Data Acquisition and Preprocessing:
The dataset used in this study is obtained from the publicly available PlantVillage dataset on Kaggle \cite{rex2023plantdisease}. To maintain consistency all images are resized to a standardized dimension of 260x260 pixels. The dataset is divided into two main segments a training set which accounts for 60\% of the data and a validation set which makes up 40\%. The validation subset is divided into two separate sets a validation set 50\% and a test set 50\%. Maintaining the integrity and reliability of model training as well as subsequent stages of validation and comprehensive evaluation relies heavily on the precise execution of a rigorous data splitting approach.

EfficientNet-B1 Model Development:
The significance of ImageNet \cite{deng2009imagenet} in advancing computer vision and image classification is undeniable, providing access to deep learning models trained on extensive datasets. Particularly in domains with limited data, such as biomedical image analysis, pre-trained models serve as a cornerstone for transfer learning \cite{pan2010survey}. This technique enhances performance by transferring broad-domain knowledge from large datasets to smaller domain-specific ones.

The EfficientNet family comprises eight models from B0 to B7. Remarkably, as model complexity increases, the growth in parameters remains moderate while precision significantly improves. Notably, EfficientNet distinguishes itself by adopting the Swish activation function over the common Rectifier Linear Unit (ReLU) \cite{tan2019efficientnet}. The primary objective of deep learning architectures is to uncover more efficient approaches with fewer models. Unlike its counterparts, EfficientNet achieves this through uniform scaling of depth, width, and resolution while reducing the model's overall size. The compound scaling technique plays a pivotal role in this process, establishing the scaling coefficients for depth, width, and resolution dimensions. These coefficients guide the transformation from the baseline to the target network \cite{tan2019efficientnet}. The key divergence between the EfficientNet base model and the EfficientNet-B1 model lies in the scaling coefficients. These coefficients dictate the degree of expansion relative to the base model, emphasizing EfficientNet-B1's increased network layers, width, and input image resolution compared to EfficientNet-B0. This scaling strategy strikes a balance between model complexity and efficiency.

Optimization employs the Adam stochastic gradient algorithm, which updates model weights and biases during training through adaptive learning rates and momentum. The EfficientNet-B1 model employs categorical cross-entropy as the loss function for multi-class classification tasks. Renowned for its effectiveness in quantifying the divergence between projected and actual class probabilities, this loss function imposes penalties for erroneous predictions, thereby facilitating effective learning. Consequently, categorical cross-entropy stands as a preferred choice for optimizing neural network models in the context of multi-class classification. The Adam algorithm operates with a learning rate of 0.0001, further enhancing optimization effectiveness.

3. RESULTS

The Performance Evaluation section provides a comprehensive assessment of the proposed method's efficacy in classifying tomato leaf diseases using the EfficientNet-B1 architecture. Conducted within a cross-validation framework with 30 epochs per fold and a batch size of 64, the evaluation tracks essential metrics like training accuracy, training loss, validation accuracy, and validation loss. Impressively, the highest validation accuracy achieved is 99.32%, accompanied by an exceptionally low validation loss of 0.02%. Notably, the fifth fold exhibits remarkable performance. The training progress and validation are visually depicted in Figure 3, highlighting consistent improvement over epochs. Validation precision stabilizes at around 98.5% to 99.5% after some fluctuations, culminating in an exceptional 99.32% accuracy for the fifth fold.

FOLD	PRECISION%	RECALL %	FI-SCORE%	ACCURACY%
FOLD 1	98.87%	98.47	98.67	98.74
FOLD 2	98.80%	98.67	98.60	98.81
FOLD 3	99.13	98.93	99.00	99.20
FOLD 4	98.87	99.07	99.04	98.98
FOLD 5	99.40	99.27	99.47	99.32
MEAN	**99.01**	**98.88**	**98.95**	**99.01**

TABLE I: Evaluation matrics results of 5 folds

STUDY	CLASSES	MODELS	ACCURACY
DURMUS et al. \cite{durmucs2017disease}	14	SqueezeNet	97.22
ZHANG et al. \cite{zhang2018can}	10	ResNet	97.19
SABROL et al. \cite{sabrol2016tomato}	6	Decission Tree 3	97.30
KARTHIK et al. \cite{karthik2020attention}	4	Attention CNN	98.00
HONG et al. \cite {9196295}	18	Densenet_Xception	97.10
THIS WORK	**15**	**Efficientnet-B1**	**99.01**

TABLE II: Performance Comparison

A comprehensive comparative analysis in Table I highlights the proposed methodology's excellence, achieving a significant accuracy of 99.01% compared to prior research. The study overcomes limitations observed in other approaches, such as data scarcity hindering SqueezeNet and inherent constraints in Densenet Xception despite its 97.10% accuracy. The article's reliability is further enhanced by its thorough presentation of dataset specifics, hyperparameters, and model selection, addressing issues like overfitting and class disparities. Utilizing rigorous cross-validation over 30 iterations, the method attains a noteworthy 99.32% validation accuracy for accurately categorizing diverse tomato diseases. In summary, this article demonstrates substantial advancement through precision, transparency, and rigorous evaluation, contributing to the field's progress.

4. DISCUSSION

The methodology being offered exhibits exceptional precision and a methodical framework, setting it apart from current research practices. By effectively addressing the shortcomings associated with alternative methodologies, this approach makes a substantial contribution to the field of tomato disease categorization. The thorough explanation of dataset characteristics, hyperparameter configurations, and model selection enhances the reliability and trustworthiness of the technique. Furthermore, the notable aspect of this approach lies in its ability to effectively tackle difficulties such as overfitting and discrepancies in class distribution.

The robustness of the suggested method is underscored by the implementation of a comprehensive cross-validation process over 30 iterations. The acquired validation accuracy of 99.32% in the sixth fold highlights the efficiency of the model in effectively classifying different tomato illnesses. In general, the study demonstrates significant advancements in the industry due to its exceptional level of accuracy, straightforward approach to technique, and rigorous evaluation protocols. This study establishes a robust basis for future progress in the categorization of plant diseases, hence promoting the development of a more resilient and productive agricultural ecosystem.

5. Conclusion

This study effectively addressed the challenge of precise disease detection in tomato plants by employing deep learning techniques. The primary objective was to develop a model capable of identifying various diseases on tomato leaf surfaces in real time, thereby enabling opportune interventions to prevent extensive crop losses. Utilizing deep learning algorithms within a robotic framework, the research intended to achieve this objective in a methodical manner. This method exploited the power of deep learning, specifically the EfficientNet-B1 architecture, to classify fifteen distinct categories of tomato plant diseases, including those that affect healthy foliage. Using the PlantVillage dataset, the model undertook meticulous data preprocessing to ensure standardized inputs for training and validation. Utilizing five-fold cross-validation allowed for comprehensive model evaluation, thereby enhancing reliability and performance assessment. The results show that the EfficientNet-B1 model can classify tomato plant diseases with exceptional precision. Metrics such as precision, recall, F1-score, and accuracy consistently exceeded 98%, and in some instances, even surpassed 99%. This accuracy surpasses previous research and demonstrates the efficacy of the proposed method. In the fifth fold, validation accuracy reached 99.32%, demonstrating the model's ability to accurately identify numerous tomato leaf diseases. In addition, the importance of early disease detection in tomato cultivation is emphasized. Given the rising global demand for tomatoes and the economic repercussions of crop losses, innovative technologies such as deep learning play a crucial role. The proposed method aligns with the trend of precision agriculture, optimizing crop management, minimizing pesticide reliance, and increasing overall productivity. Through deep learning, the researchers accurately classified tomato leaf diseases, which holds significant implications for agriculture. It contributes to efficient disease management through the power of artificial intelligence, ensuring healthier crop yields, increased food security, and sustainable agricultural practices. Future efforts could implement the model in the field, further revolutionizing precision agriculture and plant disease detection.

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7. CONTRIBUTION

	Sharia Arfin Tanim	**Zahid Hasan Anik**	**Shahriar Mushficul Islam**		**Contribution (%)**
	20-42096-1	20-42284-1	19-39497-1		
Conceptualization	60%	40%	0%		100 %
Data curation	50%	50%	0%		100 %
Formal analysis	60%	40%	0%		100 %
Investigation	100%	0%	0%		100 %
Methodology	60%	40%	0%		100 %
Implementation	70%	30%	0%		100 %
Validation	80%	20%	0%		100 %
Theoretical derivations	30%	70%	0%		100 %
Preparation of figures	100%	0%	0%		100 %
Writing – original draft	50%	50%	0%		100 %
Writing – review & editing	20%	80%	0%		100 %