Comparative Analysis of Tomato Disease Classification: A Performance Evaluation of CNNs and Traditional Classifiers with Explainable AI

Abu Bakar Hasnath, Sabista Ifraj, Sameha Kamrul, Sania Azhmee Bhuiyan,
Md Humaion Kabir Mehedi, Farah Binta Haque and Annajiat Alim Rasel
Department of Computer Science and Engineering, BRAC University, Dhaka, Bangladesh
abubakarhasnath2002@g.bracu.ac.bd, sbifraj123@g.bracu.ac.bd, sameha.kamrul@g.bracu.ac.bd,
saniaazhmee98@g.bracu.ac.bd, humaion.kabir.mehedi@g.bracu.ac.bd, farah.binta.haque@g.bracu.ac.bd,
annajiat@gmail.com

***Abstract*—Plant leaf disease is one of the reasons behind crop losses worldwide and it has a bad impact on the economy globally. Across the world specifically for tomato plants, farmers are struggling to keep their crops healthy, with the hope of early detecting specific diseases caused by bacteria, viruses, fungi, worms, and insects so that they can take necessary steps to promptly avoid disease spreading throughout the farmlands. To fight this, smart agriculture solutions are emerging and they consist of Machine Learning and the Internet of Things implementations for disease detection and control. Moreover, explainable AI is also emerging nowadays to interpret and observe the prediction mechanism of leaf disease by various image classification models, all these technologies help to find the best solutions to stop tomato leaf diseases from spreading across the field. Nowadays, because of an increasing number of available image classification techniques, a need to determine which image classification model and for what reason is best at detecting tomato leaf disease with high accuracy has become a necessity. Accurately, identification of the leaf disease is essential and also crucial for economic purposes as automation can save hours of manual labor work. In this paper, we have compared and analyzed the performance of InceptionResNetV2, inceptionv3, ResNet50, VGG16 and the Vision transformer for tomato leaf disease classification and explored which region of leaf these models focus for classification using explainable AI. Our results showed that InceptionResNetV2 was able to score the highest accuracy and Vision Transformer was able to score the lowest accuracy. Additionally, we used lime_image from the lime library to study if the model with the highest accuracy was producing results based on the correct regions of the leaves. In the future, further research might benefit from using our workings to examine several variables to identify leaf infection early on and safeguard crops.**

***Index Terms*—Leaf Disease; AI; InceptionResNetV2; Inceptionv3; ResNet50; VGG16; Vision Transformer; explainable ai;**

I. Introduction

The global agricultural landscape stands at a critical juncture, grappling with the perennial challenge of minimizing crop losses induced by diseases, a predicament that significantly impacts both the economy and food security. Among the myriad of crops susceptible to disease, the tomato, an indispensable component of various cuisines and an economic cornerstone for many regions, confronts a spectrum of ailments that undermine its yield and quality.

In response to this pressing concern, the fusion of cutting-edge technologies, notably the synergy between Internet of Things (IoT) frameworks and machine learning paradigms, has ushered in a new era of "smart agriculture". This paradigm shift has been characterized by a concerted effort to harness the potential of data-driven approaches for early disease detection, precision farming, and targeted interventions.

Central to this technological revolution is the realm of visual-based machine learning methods, which serve as the vanguard in real-time disease identification and diagnosis in agricultural settings. Within this domain, Convolutional Neural Networks (CNNs) have emerged as a cornerstone, demonstrating considerable efficacy in discerning patterns indicative of various tomato diseases. However, despite their widespread adoption and success, the burgeoning field of Vision Transformers, revered for their prowess in classification tasks across diverse domains, remains relatively uncharted in the sphere of plant pathology applications, including tomato disease classification.

This research endeavors to bridge this gap through a meticulous comparative analysis of tomato disease classification methodologies. The principal objective is to delineate a comprehensive evaluation that juxtaposes the performance of Convolutional Neural Networks (CNNs) against that of traditional classifiers, while concurrently delving into the unexplored potential of Vision Transformers in this domain. By rigorously assessing these methodologies, this study seeks to unravel their respective strengths, limitations, and overall efficacy in accurately identifying and classifying a myriad of tomato diseases prevalent across different cultivars.

Drawing inspiration from seminal works such as "PlantXViT", where a novel Vision Transformer enabled Convolutional Neural Network was proposed for plant disease identification, this research endeavors to build upon this foundation. The proposed model aims to amalgamate the innate strengths of CNNs and Vision Transformers, aspiring to create a robust framework proficient in identifying and categorizing diverse manifestations of tomato diseases across varied environmental conditions [1].

Furthermore, in resonance with recent advancements in automated plant disease classification utilizing Vision Transformers, this paper aspires to contribute to this burgeoning field by conducting a thorough comparative analysis. It seeks to address pertinent queries raised in contemporary research, pondering the viability of lightweight architectures to maintain performance standards while catering to the exigencies of real-time applications, considering computational costs, and efficacy in disease recognition [2].

Agriculture is one of the key values of the economy, and in this era tomato has a significant role in our day to day life. The consumption of tomato has a variety in our dining as soup, as can product, as sauce and many more. Tomatoes grow normally everywhere in the dry soil. Eventually, 98 percent of the farmers grow tomatoes on their lands. So, to effectively plant those tomatoes, it is really necessary to avoid the leaf disease which can hamper the growth of the tomato and break the consistency in the economy. However, this kind of leaf disease can be detected with the help of analysis of the leaf, roots, stems, seeds. Mostly, the occurrence happens on the leaves, so if we are able to diagnose the leaves of the plant we will be able to take precaution before. Early detection of the disease is really important for producing healthy products [2]. In some cases, farmers are not able to detect the symptoms of the plant disease because it needs detailed analysis, which requires a large amount of data set. This is why we are making a hybrid dataset which consists of a plant village dataset and tomato disease dataset. Moreover, we tried to implement a model which is considered to be great according to the accuracy after comparing with quite a few models. Nevertheless, this necessitates a high level of experience from specialists, increasing the intensity of artificial labor and delaying the optimal period for disease prevention [2].

Automatic detection systems would be very much preferable in this kind of direction, so that major precautions could be taken before it's too late. Disease like, early blight caused by fungus Alternaria solani. This causes dark spots in the lower level of the leaf and leaves a yellow shadow on it. Secondly, late blight, caused by oomycete Phytophthora infestans. However,It leaves white marks on the leaves and it causes damage to the leaves very quickly. Thirdly, Septoria Leaf Spot which is caused by fungus Septoria Lycopersici. Furthermore, It causes small dark spots under the leaves. Fourthly, Speck and Spot which is caused by bacteria also make small dark spots and it takes quality of time to spread. Lastly, Tomato Mosaic virus which causes mottling and discoloration of leaves. To manage these leaves with care so that good products are produced, a good management of tomato leaves is really necessary which involves several strategies, including using disease-resistant tomato variants, using proper sanitation, taking care of the air circulation to minimize the impact of the disease. The models that are used in this paper consist of different comparisons within it, consisting of InceptionResNetV2, inceptionv3, ResNet50, VGG16 and the vision transformer modeling. Enhancing this comparison we can move to a grater approach which involves the explainable AI approach also. When crops are first infected with a disease, rapid access to information on agricultural diseases can help detect the cause of the disease, identify the disease, and identify lightness of the disease. Minimize the usage of pesticides while, to some extent, also preventing and controlling illness.

II. Literature Review

The field of tomato leaf disease detection, as illustrated by the various studies, and accuracy in tomato leaf disease detection has led to a lot of research contributing uniquely to the field. For instance, the modified AlexNet CNN model, as explored in research, demonstrates a high accuracy of 96% in classifying tomato leaf diseases, leveraging a Kaggle dataset of 18,345 training images. This model's integration of convolution layers and fully connected layers, combined with dropout values, illustrates an innovative approach to disease classification suitable for mobile applications [3]. Similarly, T Psao introduces a hybrid model, FC-SNDPN, incorporating ResNet, ResNeXt, DenseNet, and Dual Path Networks. This model achieved an impressive F1 score accuracy of 97.59%, evidencing the potential of complex architectures in enhancing classification performance [4]. In the same vein, M. Abdul explores the use of genetic algorithms with CNNs, utilizing the PlantVillage dataset to achieve accuracy rates of 97.7% and 98.6%, showcasing the effectiveness of hybrid models in disease detection. Moreover, the simplicity and efficiency of DCNNs are highlighted in a paper which achieved a 98.40% accuracy rate. This research underscores the potential of fewer-layer models in achieving high accuracy in a reduced time frame [7]. Contrastingly, another paper [8] presents an android-based application system, utilizing image processing techniques like GLCM and SVM, achieving accuracies up to 100% in certain categories. This approach exemplifies the role of mobile applications in facilitating disease identification. In another work which is quite similar to [6], combines CNNs with genetic algorithms, further emphasizing the trend towards hybrid models in this field [9]. In our paper we have used ResNet-50 as it seems to perform quite tremendously as research on the ResNet-50 model with data augmentation reflects another dimension of this exploration, achieving a 97% accuracy rate and highlighting the importance of dataset diversity in training models [10]. The diverse methodologies and results presented in these papers collectively explored to optimize the detection and classification of tomato leaf diseases. The convergence of techniques ranging from deep learning architectures to genetic algorithms and mobile applications demonstrates the multifaceted nature of this research area. Each study contributes in a different way but gradually constructing a more comprehensive understanding of how to best tackle the challenge of disease detection in tomato plants. In conclusion, the study tomato leaf disease detection each contributes to an ever-evolving understanding of how to efficiently and accurately identify plant diseases. From the utilization of advanced CNN architectures and hybrid models to the integration of mobile applications, these studies collectively underscore the dynamic and innovative nature of research in this area.

III. Dataset

We build a hybrid dataset by combining the Tomato Disease dataset collected from the Kaggle dataset repository and the Plant Village dataset from the Kaggle dataset repository. The Tomato disease dataset consists of 20000 images, which consists of late blight, early blight, septoria leaf spot, Tomato yellow leaf curl virus, Bacterial spot, target spot, tomato mosaic virus, and leaf mold, which are some of the most common classes of tomato disease. The tomato disease dataset has a variety of images that consist of different types of disease data. This includes multiple sources, and a diverse collection includes different stages of symptom images, as this dataset contains images from multiple sources some of the image files were incorrect, not from credible, sources, and sometimes even corrupt, we manually cleaned the dataset to get rid of such unusable images. On the other hand, the plant village dataset consists of 20600 images, which include many different plants such as tomatoes, potatoes, and strawberries and different types of plant diseases. This hybrid dataset used by this research was built by combining 10 classes from the plant village dataset including Bacterial spot, Early blight, healthy, Late blight, Leaf mold, Septoria leaf spot, spider mites, Target Spot, Tomato mosaic virus, Yellow Leaf Curl Virus, and Powdery mildew which is one class taken from Kaggle Tomato disease dataset. Adding to it, the plant village dataset is a comprehensive one as it also has a collection of images which consists of healthy and diseased dataset images. Moreover, it also offers a wide range of plant types and conditions for automated direction and diagnosis of the plant.

IV. Methodology

A. Data preprocessing

Data preprocessing consists of a variety of workflows to bring the data to a position where it can be utilized to test the models. Data needs to be cleaned up before it heads to utilization and balance as if it is an imbalanced dataset. The dataset has a lot of irrelevant parts like shadow and sizing issues as each one may not be the same size but while giving it to test the model, we need to make sure all the data is of the same size. The dataset was cleaned manually, and the Tomato disease dataset contained some corrupt and irrelevant images. OpenCV is used for resizing the image to reduce computational load and ensure consistency. The target size of the resizing image was 224 × 224. Thereafter, normalizing the image pixels into a common one so that every image is a standard size which will allow testing the data in a structured manner. Moreover, rotating the data in the range of 30, width shift range 0.2, shear range 0.2, zoom range 0.2 and flip mode was set to nearest so that every pixel is of the same rotation and zoomed and shifted in a right direction, which will ensure augmentation of the data. These parameters were set using the ImageDataGenerator class imported from the Keras library. Soon after that oversampling or undersampling was utilized to target the imbalance data into a balanced one. After that, proportioning the data for training to 80% of total images, validation 10%, and testing 10% to see the result according to it and to compare how the models are working. Lastly, The quality of the data is worth working with or not and needs to be checked.

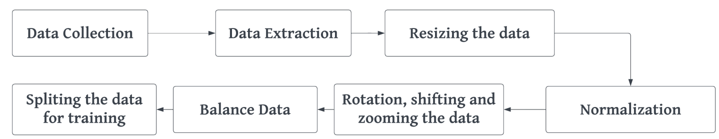

Fig. 1. Preparation phase of Data

B. Models:

a) InceptionResNetV2: InceptionResNet V2 is a deep convolutional neural network architecture which combines two architectures Inception and ResNet architecture. It is developed by Google's research architecture team. Inception modules are specialized on multiple convolutional networks of different sizes with the same layer. It works best in utilizing the resource to capture both local and global features. A key feature, Residual connection involves adding skip connections that allow gradients to propagate more effectively during training. This architecture stacks multiple inception block, which contains parallel branches of convolutional with different kernel size (1*1), (3*3), and (5*5). With each inception block, residual connection intercorporate. This network typically ends with global pooling and connected layers and a softmax layer for classification. However, during its development, InceptionResNet v2 demonstrated state of art performance on various benchmark datasets for image classification and computer vision task implementation.

b) InceptionV3: This architecture is the evolution from InceptionResNet V2. This module allows the network to capture features at different scales simultaneously. By using filter sizes in parallel, the network can capture features at different scales and complexity allowing for richer presentation. However, inception modules are the key component of Inception architecture. Moreover, Auxiliary classifiers are also added to mitigate the layers during the training process to reduce the vanishing gradient problem. This module begins with standard convolution layers for initial feature extraction. This architecture is widely used for classification, object recognition, and feature extraction.

c) ResNet50: ResNet50 is a deep convolutional neural network architecture, which works in depth and residual connections. It is developed by the Microsoft Research team. It is a part of ResNet and contains 50 years. Here ResNet50 contains residual blocks and each block contains several layers. Residual block consists of skip connections that can bypass one or more layers. In the block, a bottleneck architecture is used, which is (1*1), (3*3), (1*1). The (1*1) reduce the dimensions, (3*3) convolutions capture spatial information, and (1*1) expand the dimensions. This architecture's design enables the training of deeper neural networks. ResNet50's balance of depth and computing efficiency makes it, along with other ResNet versions, a popular choice for image classification tasks, transfer learning, object identification, and image feature extraction. In the field of deep learning, its design has become a standard for a variety of vision-related applications.

d) VGG16: VGG16 is convolutional neural network architecture. It is developed by Visual Graphic Group (VGG) at University of Oxford. It consists of 16 layers and 13 convolutional layers and 3 fully connected layers. This architecture, have multiple convolutional layers with 3*3 filter, which is situated one after one. Moreover, max pooling layers with 2*2 filters and 2 are convolutional layers to reduce spatial dimensions and dominant features. These layers are followed by fully connected layers at the end of the network. Firstly, VGG16 is initiated with an input layer, where the image is taken inside. The network is constructed from up of numerous convolutional layer stacks. Every stack has a max pooling layer after it. As data passes through the network, convolutional layers perform the function of feature extractors, extracting low-level to high-level features from the input image. Max pooling layers preserve the most significant features in the feature maps while decreasing their spatial dimensions. The feature maps are flattened and sent through fully connected layers at the conclusion of the network, where they are classified using the characteristics that have been learnt. However, VGG has a simple architecture with small convolutional layers, which makes it easy to understand.

e) Vision Transformer: Vision Transformer (ViT) is an architecture for image classification and it was designed for Natural Language Processing (NLP) but later it started digging into computer vision. This novel architecture reads the image sequence and processes it using a transformer encoder. Firstly, for input, the image is converted into fixed-size non-overlapping patches. Each patch is linearly embedded into a lower-dimensional vector space, similar to NLP embedding tasks. After that, sequence of the patch embeddings, with the position embedding, is fed into transformer code to act properly. The final output token is classified by processing it via a classification head, which normally consists of one or more entirely connected layers. The final output token is typically the first token or a chosen classification token. Likewise, ViT can also be trained on the large dataset as ImageNet the way it was used in this paper and fine tuned on smaller and specific datasets so that it could improve the performance. It has shown some promising results with the image classification.

f) Explainable AI: Explainable AI is one of the models which acts really well in prediction and for this paper, disease detection is really going to have a great impact from it. However, it eases the complex AI models into explainable ones. So that one can read and understand how that model works. Adding to that, methods like SHAP (SHapley Additive exPlanations), and LIME (Local Interpretable Model-agnostic Explanation) plays an important role to calculate the importance of input features. This feature indicates how each of the features indicates in models prediction. In order to explain how the model came to a certain conclusion, XAI approaches produce interpretable outputs, such as feature significance ratings, visualizations, or human-understandable rules. Moreover, This XAI provides insights into the decision making process of AI models, with the critical domain like healthcare, finance and autonomous systems.

Each of the models is run through the hybrid dataset and compared with each one to have a clear view upon the detection process which will be best fit to use it. Enhancing the data and splitting those into train, validation and test is quite a necessary step to utilize the models. After that, separating the generator and validating it for text data is one of the essential steps for model validation. Soon after that, a base model is implemented according to which domain it is working on, however customizing it adds new values to it. When testing ends, the learning phase of the model starts to grab the changes according to the model run. Moreover, tuning is one of the essential steps of the model processing to have specified results. Furthermore, evaluation of the model is needed to confirm how this model is working and how all the other aspects of the model are working. Lastly, the result that is generated gives a clear view to the processing of the data and model.

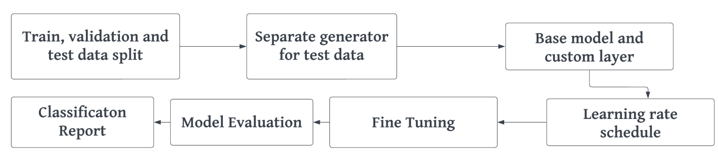

Fig. 2. The operational way of the models

V. Result analysis

The work precisely states that CNN models really have a great impact on the early direction and taking precaution beforehand. In this paper, comparing the crop disease and different methods to learn which works better is significant as shown in TABLE I.

TABLE I
Model Accuracy

Model	Accuracy	Precision	Recall	F1 Score
InceptionResNetV2	99.17%	0.99	0.99	0.99
InceptionV3	95.44%	0.96	0.95	0.95
ResNet50	92.97 %	0.94	0.93	0.93
VGG16	82.76%	0.84	0.83	0.83
Vision Transformer	30.21%	0.09	0.3	0.14

In this paper, each of the models run for the data set has set some precision, recall, f1-score and support score. On this basis some graphs are made, to make understand which one of the models has worked better as shown in the Fig.3, Fig.5, Fig.7, Fig.9.

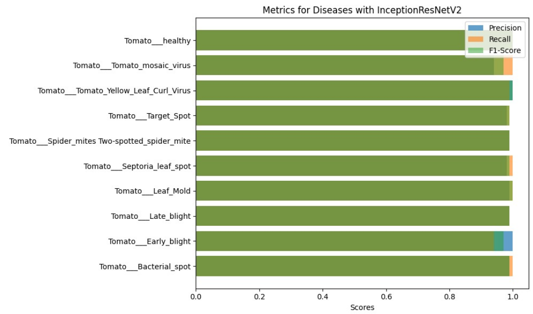

Fig. 3. Disease Patterns Matrices in InceptionResNetV2

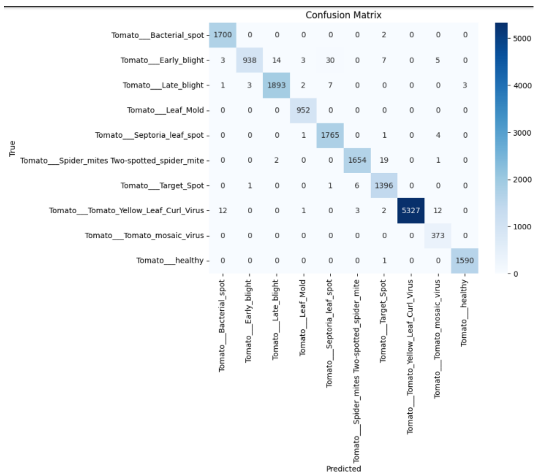

Fig. 4. InceptionResNetV2 confusion matrix

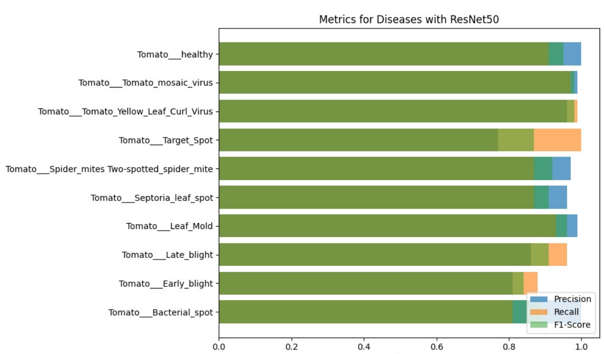

Fig. 5. Disease Patterns Matrices in VGG16 ResNet50

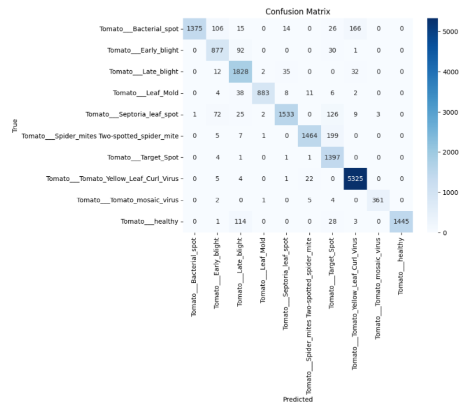

Fig. 6. ResNet50 confusion matrix

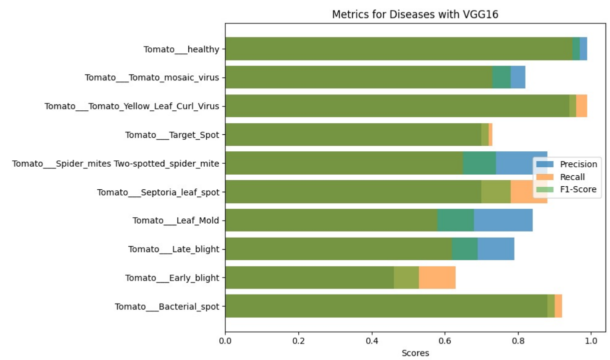

Fig. 7. Disease Patterns Matrices in VGG16

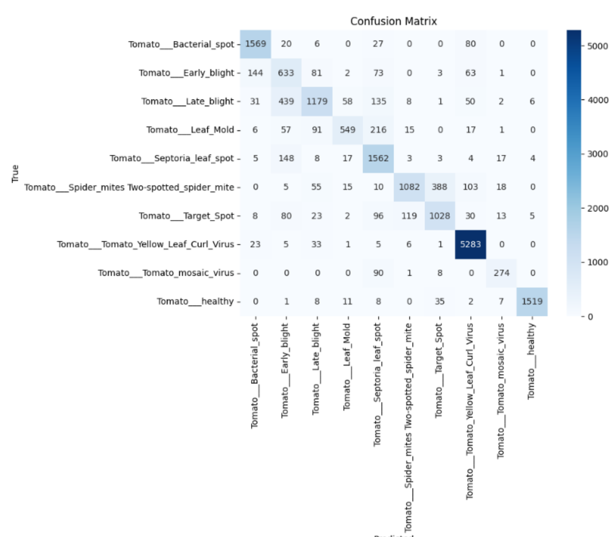

Fig. 8. VGG16 confusion matrix

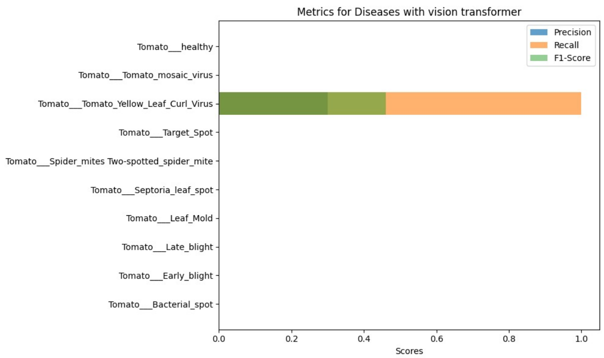

Fig. 9. Disease Patterns Matrices in vision transformer

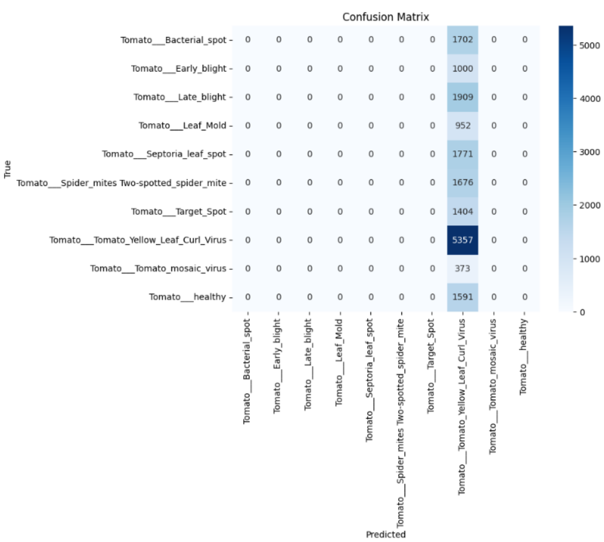

Fig. 10. Vission Tranformer confusion matrix

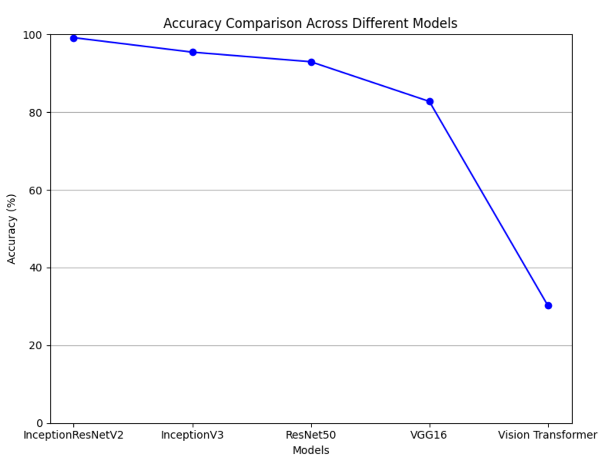

Fig. 11. Accuracy measures of different methods

The InceptionResNetv2 has an accuracy of 99.17%, Inceptionv3 has an accuracy of 95.44%. Both of the models can have a great impact in the life span of the farmer as it could be helped in detecting the disease in an earlier manner. Moreover, the other models. ResNet50 has also done precisely well as this has accuracy of 92.97%. On the other hand, VGG16 and vision dataset has accuracy of 82.76% and 30.21% respectively. In the Fig.7 a combined graph is given with the model to show which is performing better among all those. CNN significantly affects tomato plant leaf disease detection by improving result production.

Fig. 12. Original image

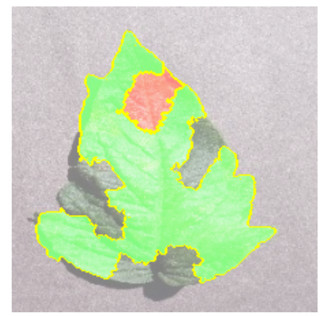

Fig. 13. After detection the effected areas

In this paper, we have analyzed the interpretability of InceptionResNetV2 image classifier on our hybrid tomato disease dataset using explainable AI. We have used Lime (Local Interpretable Model-agnostic Explanations), a very capable machine learning technique to shed light on the process of decision making of our InceptionResNetV2 because this model was able to classify new tomato leaf diseases with highest accuracy. Lime analyzes the input image and observes the resultant changes by the specified model's output to accurately highlight the regions of the leaf image that contributed toward the decision making of the specified classifier model. In this paper we have shown two images side by side, the first one is an original image of a Tomato Early Blight disease and the second one is the image output of lime. The green region on the second image highlights the regions based on which the InceptionResNetV2 classified the image to fall under Early Blight class, the more darkened region means this region had the highest influence for the decision making. We can conclude that InceptionResNetV2 was making all the decisions correctly based on our observation using lime output, as we can see that the majority of the leaf area was highlighted and very low outside area was highlighted by lime, this explains why this model was able to output results with highest accuracy. This technique enhances the transparency behind machine learning model decisions and also contributes valuable insight into the robust architecture and classification capabilities of popular deep learning classification techniques.

VI. Limitation

For efficient training, CNNs require a lot of labeled data. Insufficient generalization of models or overfitting might result from insufficient data. CNNs require a lot of processing power to train, especially deeper structures, which makes the process time- and resource-consuming. CNNs use pooling layers to ensure translation invariance, however this might result in a loss of spatial information. They may thus find it difficult to complete accurate localization assignments. CNNs may overlook more comprehensive contextual information in their focus on local information inside receptive fields. Deeper networks could find it difficult to comprehend the global context. CNNs' robustness may be impacted by differences in input data, such as noise, occlusion, or changes in illumination and orientation. It might be difficult to comprehend why particular predictions are made by CNNs. They are frequently regarded as interpretability-deficient "black-box" models. Rather than looking at the dark side of the architecture, exploring the brightside would help to work efficiently.

VII. Conclusion

Based on a number of experiments carried out for this study, the preprocessing strategy and classification technique that use the CNN algorithm with an architecture based on InceptionResNetv2 can be a reliable source to detect the leaf disease. The average precision value is 99%, recall value is 99%, f1-score is 99%, which demostrates that this models works precisely better with the image. Nevertheless, tomato producers or farmers are anticipated to find value in the study's findings. Users can quickly determine the various ailments these plants are afflicted with. In order to incorporate inceptionv3, ResNet50, VGG16, vision transformer and other CNN architectures that outperform InceptionResNetV2 for faster training and more accurate prediction generation, more experimental setups and structural alterations to these CNN architectures are advised for use in future studies.

References

[1] Thakur, P. S., Khanna, P., Sheorey, T., & Ojha, A. (2022). Explainable Vision Transformer Enabled Convolutional Neural Network for Plant Disease Identification: PlantXViT. arXiv preprint arXiv:2207.07919.

[2] Borhani, Yasamin & Khoramdel, Javad & Najafi, Esmaeil. (2022). A deep learning based approach for automated plant disease classification using vision transformer. Scientific Reports. 12. 11554. 10.1038/s41598-022-15163-0.

[3] A. O. Anim-Ayeko, C. Schillaci, A. Lipani, "Automatic blight disease detection in potato (Solanum tuberosum L.) and tomato (Solanum lycopersicum, L. 1753) plants using deep learning," *Smart Agricultural Technology*, vol. 4, pp. 100178, 2023, ISSN 2772-3755, DOI: 10.1016/j.atech.2023.100178. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2772375523000084

[4] H.-C. Chen, A. M. Widodo, A. Wisnujati, M. Rahaman, J. C.-W. Lin, L. Chen, and C.-E. Weng, "AlexNet Convolutional Neural Network for Disease Detection and Classification of Tomato Leaf," *Electronics*, vol. 11, no. 6, p. 951, 2022, ISSN 2079-9292, DOI: 10.3390/electronics11060951. [Online]. Available: https://www.mdpi.com/2079-9292/11/6/951

[5] Huang, X., Chen, A., Zhou, G., Zhang, X., Wang, J., Peng, N., Yan, N., & Jiang, C. (2022, June). Tomato Leaf Disease Detection System Based on FC-SNDPN. Multimedia Tools and Applications, 82. https://doi.org/10.1007/s11042-021-11790-3

[6] Moussafir, M., Chaibi, H., Rachid, S., Chehri, A., Abdessamad, E. R., & Jeon, G. (2022, June). Design of efficient techniques for tomato leaf disease detection using genetic algorithm-based and deep neural networks. Plant and Soil, 479, 1-16. https://doi.org/10.1007/s11104-022-05513-2

[7] Anandhakrishnan, T., & Jaisakthi, S. M. (2022). Deep Convolutional Neural Networks for image-based tomato leaf disease detection. Sustainable Chemistry and Pharmacy, 30, 100793. https://doi.org/10.1016/j.scp.2022.100793

[8] Ur Rahman, S., Alam, F., Ahmad, N., & Arshad, S. (2022, September). Image processing-based system for the detection, identification, and treatment of tomato leaf diseases. Multimedia Tools and Applications, 82. https://doi.org/10.1007/s11042-022-13715-0

[9] N. K. E., K. M., P. P., A. R. and V. S., "Tomato Leaf Disease Detection using Convolutional Neural Network with Data Augmentation," 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp. 1125-1132, doi: 10.1109/ICCES48766.2020.9138030.

[10] H. Kibriya, R. Rafique, W. Ahmad and S. M. Adnan, "Tomato Leaf Disease Detection Using Convolution Neural Network," 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST), Islamabad, Pakistan, 2021, pp. 346-351, doi: 10.1109/IBCAST51254.2021.9393311.