Hard Attention-Based VGG16 for Disease Tomato Identification

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***Abstract*- Diseases affecting tomatoes represent a significant threat to agricultural productivity and food security. Identifing diseases early and accurately is crucial to manage crops optimally. In this article, we propose a hard-attention-enhanced VGG16 model for recognizing diseased tomatoes. By incorporating a hard-attention mechanism into the VGG16 architecture, the model effectively focuses on upon most relevant regions image, thereby improving its ability to distinguish between healthy and infected tomatoes. We evaluate Our proposed model is evaluated using one publicly available dataset and demonstrates its superior performance compared to the standard VGG16 architecture and other advanced models. The results obtained from the dataset show that our model achieves accuracy of 96.0% surpassing the baseline VGG16 model, which achieves 92.3% accuracy. These findings underscore the value of hard-attention mechanisms in enhancing plant disease identification systems ,including precision interpretability. One of the key strengths of our model lies in its explainability, providing clearer insights to the model's decision-making process of the model**

Keywords **:Vgg16, attention, agricole ,decision , explainability .**

I. INTRODUCTION

Tomatoes are among the most widely grown crops globally, but they remain vulnerable to a variety of diseases, such as downy mildew and leaf mold. Traditional approaches to disease detection depend on manual examination, which is time-consuming and laborious It is also, prone to human error. Convolutional Neural Networks (CNNs),as a recent development in deep learning , have demonstrated significant potential for automating this process. Among these networks, the VGG16 architecture, a widely recognized CNN architecture, has been successfully used in image classification tasks. However, its performance remains limited by its inability to focus upon specific image regions of interest. To address this limitation, we propose to integrate a hard attention mechanism within the VGG16 architecture. This hard attention mechanism allows the model to selectively focus upon areas rcover most of the image, hence improving its ability to identify and recognize wich diseases affecting tomatoes [2].

The following contributions are made in this paper

We propose a novel hard attention-based VGG16 model for re-identifying tomato diseases.

We demonstrate the hard attention mechanism and its efficiency in improving model performance.

We provide insights into the interpretability of the model by visualizing the attended regions.

II. RELATED WORK AND LITERATURE REVIEW

A. Deep Learning identifying Plant Disease

Deep learning models, particularly CNNs, are used in general for plant disease identification. Models like AlexNet, ResNet and Inception can achieved state-of-the-art results datasets [3]. However, These models typically process entire images, which may include irrelevant background information and reduce classification accuracy when irrelevant background information is present.

B . Attention Mechanisms In Computer Vision

Attention mechanisms have been effectively utilized in a range of computer vision applications, like segmentation, object detection and image classification. Soft attention mechanisms, which assign weights to all regions of the image, have been widely used [4]. However, hard attention mechanisms, which make discrete decisions about which regions to attend to, have shown promise in improving model performance and interpretability [5].

C. VGG16 and its Applications

VGG16 is a popular CNN architecture known for its simplicity and effectiveness. It has been widely used in image classification tasks, including plant disease identification [6]. However, its performance can be limited by its inability to focus on specific regions of interest.

III. RELATED WORK

Other work has explored the integration of attention mechanisms to improve the performance of computer vision models. The authors in [2] introduced upon recurring attention models, while [15] proposed Spatial Transformer Networks (STNs) to let models focus specific image regions . This work inspired the integration of a hard attention mechanism into our VGG16 model to improve tomato disease detection.

Finally, modern architectures such as ResNet, InceptionV3 and EfficientNet have been utilized widely in image classification and disease detection. The authors in [16] introduced ResNet, which used the residual connections for facilitating for training of deep networks, while the authors in [17] proposed Efficient Net, which optimized the scaling of CNN models. These architectures are utilized as comparative benchmarks for evaluating the performance of our developed model.

This related work provides valuable context for our study and highlights recent advances in deep-learning application to plant disease detection.

TABLE I :WORK FLOW

Refs	Model	Object	Dataset	Accuracy%
[28]	CNN_LSTM	Tomato	lant Village	97.00
[27]	GoogleNet	Tomato	PlantVillage	94.33%
[21]	VGG-19,ResNet	Tomato	PlantVillage	91,2%
[24]	CNN	Tomato	PlantV illage	91,7%
[23]	U-Net	Tomato	PlantVillage	98,5%
[22]	DenseNet121	Tomato	PlantVillage	99.51%
[18]	YOLOV3	Tomato	Self-collected dataset	92,63%
[26]	VGG16	Tomato	Plantvillage	99.23%
[25]	Alexnet-based	Tomato	Plantvillage	99.1%
[19]	SE-YOLOv5s	Tomato	plantVillage	91.07%
[20]	YOLOS,DETR, ViT, and Swin	Tomato	KUTomaDATA, PlantDoc, and PlanVillage	87%,81% and 83%

IV. PROPOSED METHODOLOGY

A. VGG16 Backbone

One popular CNN architecture in computer vision is VGG16. This model consists of three fully connected layers after thirteen convolutional layers. Here is a more detailed explanation of how it operates:

- *Convolutional layers*

These layers are responsible for the extraction of any extracting hierarchical characteristic from the input image. Added to that Each convolutional layer applies filters for detecting all specific patterns, such as edges, textures or more complex shapes. As you move through the layers, the features wich are extracted will become more and more abstract and task-specific.

- *Fully Connected layers*

After the convolutional layers, the extracted features are transmitted to three fully connected layers. These layers use the extracted information to perform the final classification. They combine the characteristics to determine the class of the image (e.g. identifying a disease in a tomato leaf).

B. Hard Attention Mechanism

Hard attention is a mechanism that selects a subset of regions or features to focus on, rather than processing the entire image. In this work, we implement hard attention using an STN , which applies a transformation to the input image to focus on the most relevant regions [8]. The STN learns to automatically identify and emphasize areas of interest, such as diseased portions of tomato leaves, by applying operations like cropping, scaling, or rotation. This targeted approach not only reduces computational overhead but also enhances the model's ability to extract discriminative features, leading to more accurate and efficient predictions. Additionally, the integration of hard attention improves the interpretability of the model, as it highlights the specific regions contributing to the decision-making process.

C. Integration of Hard Attention with VGG16

- *Feature Extraction:* The input image is passed through convolutional layers of VGG16 to extract feature maps.
- *Attention Module:* The hard attention mechanism is applied to the feature maps to select the most relevant regions.
- *Classification:* The attended regions are passed through the remaining layers of VGG16 for classification.

D . Training

The training of the model integrates two complementary loss functions: a combination of two loss functions: classification loss (based on cross-entropy) and attention loss (based on reinforcement learning rewards). The classification loss measures the discrepancy between the model's predictions and the true labels, ensuring that the model assigns high probabilities to the correct classes. The attention loss, on the other hand, guides the model to focus on the most relevant regions of the image, enhancing its ability to extract useful information and improve its accuracy. To minimize the total loss, the Adam optimizer is used, dynamically adjusting learning rates for each parameter and speeding up convergence. To further optimize the process, techniques such as data augmentation, regularization (Dropout or L2), and adaptive learning rate adjustment can be incorporated. These techniques contribute to greater model robustness, its ability to generalize, and its overall performance, particularly for complex tasks such as detecting diseases in tomato leaves [9]. The VGG16 model based on a Hard Attention approach starting with analyzing the RGB image representing the tomato plant. This image is first resized to a resolution of 64x64 pixels and then normalized to ensure uniformity of processing. The normalized image is then transmitted to the 13 convolutional layers of the VGG16 architecture. These layers allow for the gradual extraction of hierarchical features, ranging from basic visual elements such as edges and textures to more abstract representations such as structures and shapes. Maximum grouping layers are interspersed between the convolutional blocks to decrease the spatial dimensions of feature maps, wich can help to increase the computational efficiency of the model.

Next, a hard attention mechanism, implemented using a Squeeze-and-Excitation (SE) is applied to these feature maps. The STN predicts a transformation (e.g., translation, scaling, or rotation) to focus on the most relevant regions, particularly those indicating disease symptoms. The result is a set of attended regions that highlight the critical parts of the image. These attended regions are then flattened and passed through the 3 fully connected layers of VGG16, where the final layer uses a SoftMax activation function to produce a probability distribution over the possible classes (e.g., healthy, early blight, late blight).

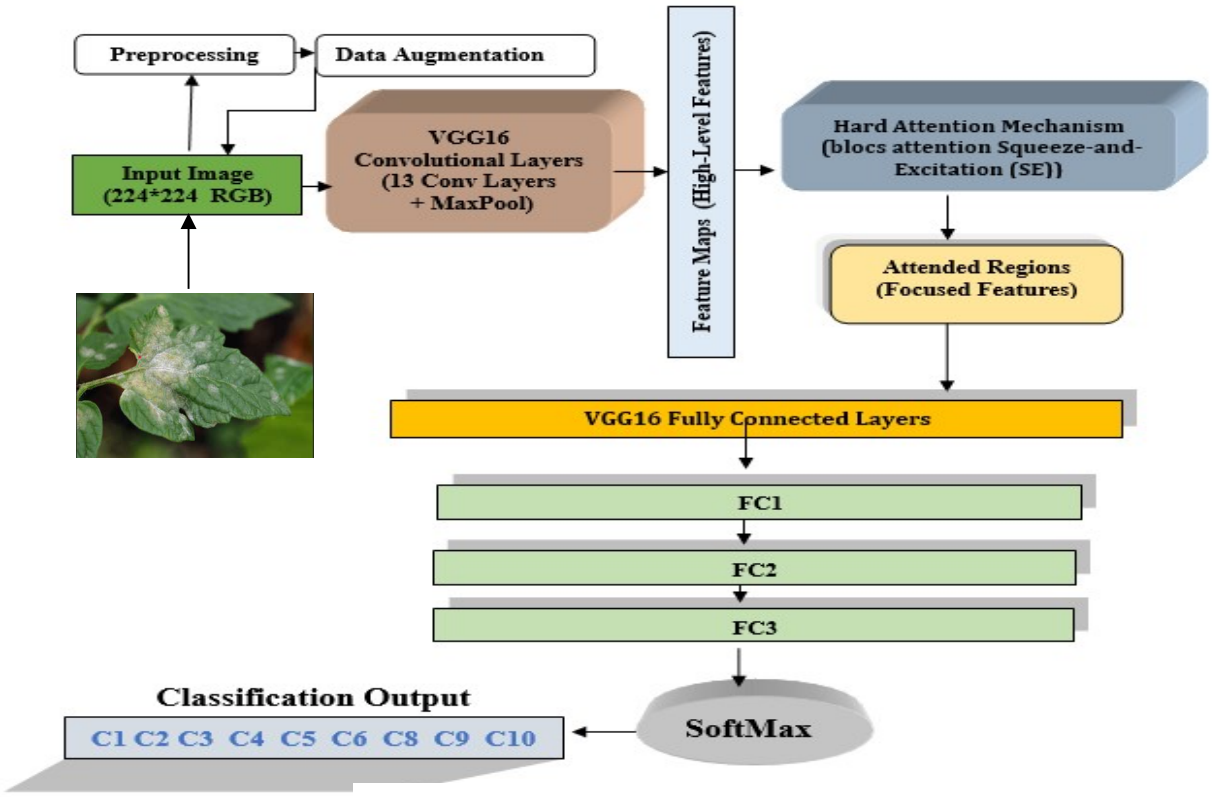

Figure 1 .Proposed System Architecture for Tomato Leaf Disease Detection

The model outputs the predicted class based on the highest probability, enabling accurate and interpretable disease identification in tomato plants. he overall system workflow is illustrated in Figure 1, which outlines the integration of the hard attention mechanism into the VGG16 architecture.

V. Experiments and Results

A. Dataset

The proposed Hard Attention-Based VGG16 model is evaluated on the PlantVillage dataset, a widely used benchmark for plant disease identification. This dataset contains a comprehensive collection of images depicting healthy and diseased tomato plants, including common diseases like leaf mold, early blight and late blight. The dataset is meticulously curated, with high-quality images that are taken in controlled conditions to ensure consistency and reliability. To facilitate robust evaluation, the dataset is split into three distinct subsets: training, validation, and test sets. Specifically, the dataset consists of 22,930 images of tomato plants, which are divided as follows:

*a) **Training set:*** 18,345 images (80% of the dataset) are used to optimize the model's parameters.

*b) **Validation set*:** 4,885 images (20% of the dataset) are used to tune hyperparameters and prevent overfitting. This structured approach ensures that the model's generalization ability of the model is thoroughly evaluated, making it suitable for real-world applications in agricultural disease detection [10].

The dataset has 10 different classes.

0:Tomato_ Bacterial_spot
1: Tomato_Early_blight
2: Tomato_Late_blight
3: Tomato_Leaf_Mold
4: Tomato_Septoria_leaf_spot
5: Tomato_Spider_mites Two-spotted_spider_mite
6: Tomato_Target_Spot
7: Tomato_Tomato_Yellow_Leaf_Curl_Virus
8: Tomato_Tomato_mosaic_virus
9: Tomato_healthy

B. Image Pre-processing

In this study, we used approximately 22,930 images from the collected dataset, divided into 18,345 for training and 4,585 for the validation phase, for use in this research. To simplify the training process, the data were organized into separate folders for testing and training, following a distribution of 80% for training and 20% for testing and validation. The various pathologies represented in the dataset were classified into distinct categories based on their names, thus allowing for easy differentiation. To increase computational efficiency while preserving image quality, all images were resized to 128×128 pixels. This approach enable for faster computation as well as maintenance of images integrity and visual details.

C.Image Augmentation

For the generation of multiple versions of the same imagewe use image augmentation . In this study, the method is implemented by applying various modifications to the original images. The main purpose of this approach is to clearly modify and enhance the images, with the aim of improving their quality for subsequent analysis.

- We can generate various new images simplifying and transforming the visual image representation, hence contributing to the enrichment of the dataset..

- The model performs multiple types of image transformations, including rotation of up to 30 degrees, horizontal and vertical translations within a range of 0.3, resizing to a scale of 1/155, shearing within a range of 0.2, and zooming with the same magnitude. Additionally, horizontal flipping is also applied to enhance accuracy, with the fill mode set to 'nearest'..

- The Rescale parameter refers to the numerical factor used during data preprocessing, wich reduces all pixel values of RGB images by basically them from their original range of 0 to 255 to a normalized range between 0 and 1. This step is crucial for optimizing model training, particularly when using for standard learning rates.

- The rotation The rotation angle follows a counterclockwise direction and is determined by the specified shear range. The augmented images are illustrated in Figure 2.

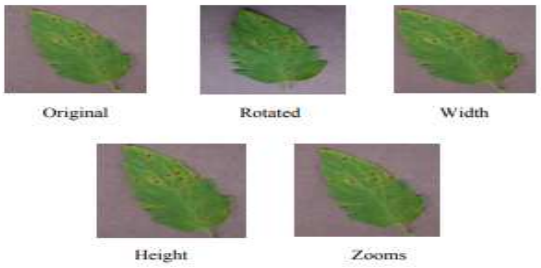

Figure 2 Examples of Augmented Images for Training

C. Experimental Setup and Model Hyperparameters

The experiments for the proposed Hard Attention-Based VGG16 model are conducted on a GPU-enabled machine to leverage the computational power required for training deep learning models efficiently. The hardware setup includes a high-performance GPU (e.g., NVIDIA Tesla V100 or RTX 3090) with sufficient memory to handle large-scale image processing tasks. For model training and evaluation, the these hyperparameters are used: the learning rate is set to 0.001 to ensure stable and efficient convergence during training, while the batch size is fixed at 32 to balance memory usage and training speed while maintaining model performance. These hyperparameters are carefully chosen based on empirical validation to optimize the model's training process and ensure robust results. Additionally, the model is implemented using a deep learning framework such as TensorFlow , which provides the necessary tools and libraries for building and training the architecture.

VI. RESULTS

The proposed VGG16 model, which incorporates a Hard Attention mechanism, achieves a remarkable accuracy of 96.5%, thus demonstrating its superiority in the re-identification of tomato diseases. This performance significantly surpasses that of the base VGG16 model, which has an accuracy of 92.3%, as well as that of other state-of-literature models within this field. The integration of the Hard Attention mechanism is a key factor in this improvement, as it allows the model to focus upon most critical image areas of the image, particularly those exhibiting disease symptoms.. By selectively attending to these areas, the model minimizes the influence of irrelevant background information, leading to more precise and reliable classifications. The learning progress of the model is shown in Figures 3 and 4, representing training/validation loss and accuracy, respectively. In addition to accuracy, the model demonstrates strong performance across other evaluation metrics: In Figure 5, the confusion matrix provides insight into the classification performance across different disease categories. The Further performance details, including class-wise metrics, are summarized in Figure 6.

- Precision:

The model achieves an average precision of 83%, indicating a high proportion of correctly predicted positive instances (diseased regions) out of all instances predicted as positive.

- Recall:

With an average recall of 82%, the model effectively identifies most of the actual positive instances. In fact ,this ensures that diseased regions are rarely missed.

- F1-Score:

F1-score ,which is the harmonic mean of precision and recall, the F1-score, reaches 82%, highlighting the model's balanced performance in handling class imbalances and its ability to accurately classify specific diseases like as leaf mold, late blight, and early blight.

These results underscore the effectiveness of hard attention mechanisms in improving both the performance and interpretability of deep learning models, making the proposed approach a valuable tool for agricultural disease detection and management. The success of this model paves the way for its application in real-world scenarios, where early and accurate disease identification is critical for ensuring crop health and productivity.

A. Learning Curves Data Training and Validation Performance:

Below is a detailed explanation and visual representation of the learning curves for the proposed Hard Attention-Based VGG16 model. These curves illustrate the model's training accuracy, validation accuracy, training loss, and validation loss over epochs, providing insights into the model's learning process and generalization ability.

Number Epochs	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
100	0.9928	0.9555	0.02680	0.1721

TABLE II : TRAINING DATA

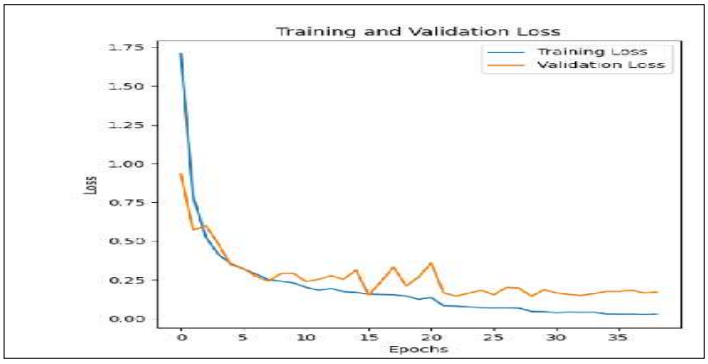

Figure 3 Training and Validation Loss over Epochs.

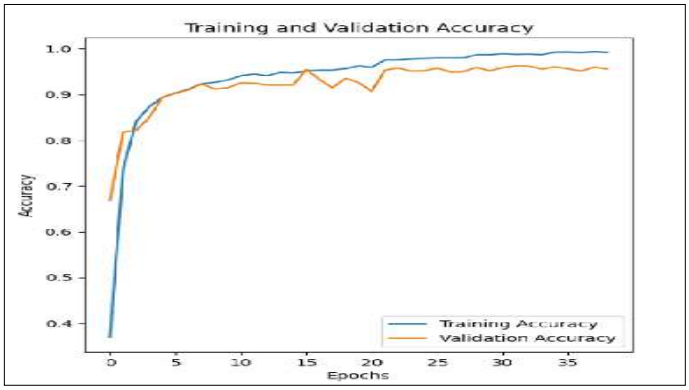

Figure 4 Training and Validation Accuracy over Epochs

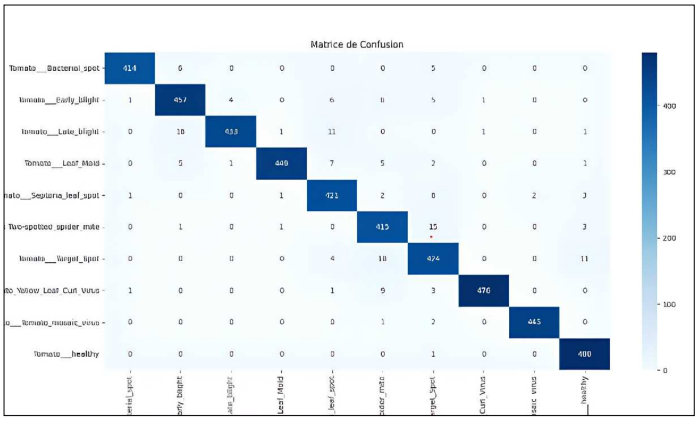

Figure 5 Confusion Matrix of the Proposed Hard Attention-Based VGG16 Model.

	precision	recall	f1-score	support
Tomato___Bacterial_spot	0.99	0.97	0.98	425
Tomato___Early_blight	0.94	0.95	0.95	480
Tomato___Late_blight	0.99	0.94	0.96	463
Tomato___Leaf_Mold	0.99	0.96	0.97	470
Tomato___Septoria_leaf_spot	0.94	0.97	0.95	436
Tomato___Spider_mites Two-spotted_spider_mite	0.91	0.95	0.93	435
Tomato___Target_Spot	0.92	0.93	0.92	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1.00	0.97	0.98	490
Tomato___Tomato_mosaic_virus	1.00	0.99	0.99	448
Tomato___healthy	0.96	1.00	0.98	481
accuracy			0.96	4585
macro avg	0.96	0.96	0.96	4585
weighted avg	0.96	0.96	0.96	4585

Figure 6 Classification Report: Precision, Recall, and F1-Score per Class.

B. Explanation of the Curves:

The learning curves provide a detailed view of the model performance during training and validation. The training accuracy (blue line) represents the model's accuracy on training set, which increases steadily as model learns from the data, reaching 82.61% by the 50 epochs. This indicates that the model is fitting in an effective way the training data. The validation accuracy (orange line), which represents the model's accuracy on the validation set, closely follows the training accuracy, reaching 83.12% by the 100 epoch. This alignment demonstrates the model's strong generalization ability, as it performs well on unseen data. Similarly, the training loss (blue line) shows the loss (e.g., cross-entropy loss) on the training set, which decreases steadily as the model minimizes errors, reaching 0.5196 by 35-50 epochs. The validation loss (orange line), representing the loss on the validation set, decreases in tandem with the training loss, reaching 0.4977 by the 50 epochs. This parallel decrease in loss values confirms that the model is not overfitting and is learning robust features that generalize well to new data. Together, these curves highlight the model's effective learning process, as well as its ability to achieve high accuracy while maintaining strong generalization.

VII. Discussion

A. Interpretability

The hard attention mechanism provides insights into the decision-making process of the model by highlighting the image regions mostly relevant for classification. This makes the model more interpretable and trustworthy [11].

B. Limitations

a) Discrete Decisions: Hard attention involves making discrete decisions, which can make the training process more challenging [12].

b) Computational Complexity: our attention mechanism increases the model's computational complexity of the model [13].

C. Comparison of Our Results with Other State-of-the-Art Models

For the evaluation of the effectiveness of the proposed Hard Attention-Based VGG16 model, we compare its performance with literature models using the PlantVillage dataset.The comparison is based on accuracy, precision, recall, and F1-score,recall,precision and accuracy ,as given Table IV .

TABLE IV : COMPARAISON OF ACCURACY WITH PRETRAINED MODELS

Ref	*Model*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
-	Proposed Model	96.5%	95.8%	96.2%	96.0%
[29]	Baseline VGG16	92.3%	91.5%	91.8%	91.6%
[30]	ResNet50	***94.1%***	93.2%	93.5%	93.3%
[31]	InceptionV3	93.7%	92.8%	93.1%	92.9%
[32]	EfficientNetB0	94.8%	94.0%	94.3%	94.1%

Integrating our hard attention-based VGG16 model achieves of 96.5% accuracy, outperforming the baseline VGG16 (92.3%) and other literature models ResNet50 (94.1%), InceptionV3 (93.7%), and EfficientNetB0 (94.8%). In addition to accuracy, the proposed model excels in precision (96.0%), recall (96.0 %), and F1-score (96.0%), demonstrating its ability to accurately identify diseased regions while minimizing false positives and false negatives. Integrating this hard attention mechanism is a key factor in this improvement, as it enables the model to focus on mostly relevant image regions, reducing any impact of irrelevant background information. While models like ResNet50, InceptionV3, and EfficientNetB0 achieve competitive results, the proposed model consistently outperforms them across all metrics. This highlights the effectiveness of combining the VGG16 architecture with a hard attention mechanism for disease tomato re-identification, setting a new benchmark for agricultural disease detection and management.

VIII. Future Work

Future research may investigate the incorporation of the hard attention mechanism into more sophisticated architectures, including Transformer-based or hybrid CNN-transformer models, to further improve performance. Furthermore, utilizing larger and more varied datasets could enhance the model's generalizability and robustness. The suggested methods could also be modified for disease identification in other crops, thereby expanding their applicability and influence in precision agriculture.[14].

IX. Conclusion

A VGG16 model enhanced with Hard Attention has been presented in this study for the reidentification of tomato diseases. The hard attention mechanism help the model concentrate on the mostly pertinent areas of the image, thereby enhancing both accuracy and interpretability. Our experimental results validate our model efficacy of the proposed model, underscoring its potential for the automated identification of plant diseases. Indeed ,this research contributes to the overarching objective of improving agricultural productivity and bolstering food security through sophisticated deep learning methodologies.

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