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Deep Learning Based Multiclass Prediction for Bell Pepper Plant Leaf Pathology

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ABSTRACT: Bell pepper (Capsicum annuum) is a globally cherished vegetable, celebrated for its nutritional richness and culinary versatility. Despite its popularity, the cultivation of bell peppers faces persistent challenges posed by various diseases that adversely impact both yield and produce quality. Identifying and predicting these diseases at an early stage is critical for implementing timely and targeted interventions to mitigate their impact and ensure a successful harvest. In recent years, the agricultural landscape has witnessed transformative advancements, particularly in the realms of computer vision and machine learning. These technological strides offer a promising opportunity to revolutionize traditional farming practices by introducing advanced tools for disease identification and prediction. This study places a focused lens on harnessing cutting-edge models, including the Vision Transformer (ViT), EfficientNet, ResNet to predict diseases affecting bell pepper leaves. These Deep learning technologies that helps special computer programs look very closely at pictures of bell pepper leaves. These programs are trained to understand all the little details in the images. By doing this, they become really good at spotting signs of possible diseases in the leaves. So, it's like having a super-smart helper that can quickly and accurately find out if the bell pepper plants might be getting sick, allowing farmers to take action early and prevent problems from getting worse. The goal of this research is to contribute significantly to the development of precise and practical tools that enable proactive disease management in bell pepper cultivation. Such tools hold the promise of enhancing the sustainability and productivity of bell pepper crops, ensuring a more secure and abundant supply of this essential vegetable for global consumption.

KEYWORDS: Bell pepper, Capsicum annuum, disease identification, prediction, Vision Transformer (ViT), EfficientNet, ResNet, deep learning, proactive disease management.

I. INTRODUCTION

The agricultural sector plays a crucial role in sustaining global food security and economic stability. Among various crops, bell pepper (Capsicum annuum) stands out as one of the most important vegetables worldwide, contributing significantly to both culinary and economic domains. However, bell pepper cultivation faces numerous challenges, with plant diseases posing a significant threat to yield and quality. Accurate and timely detection of these diseases is essential for implementing effective management strategies and ensuring crop health. Traditional methods of plant disease diagnosis often rely on visual inspection by experts, which can be time-consuming, subjective, and prone to errors. In recent years, advancements in deep learning techniques have revolutionized the field of agriculture by offering efficient and automated solutions for plant disease detection and classification. In this context, the research aims to develop a robust multiclass prediction system for bell pepper plant leaf pathology using state-of-the-art deep learning architectures, including Vision Transformer, ResNet, EfficientNet. The integration of deep learning models such as Vision Transformer, ResNet, EfficientNet offers a comprehensive approach to address the complexities inherent in bell pepper disease classification. Vision Transformer, a recent innovation in computer vision, leverages self-attention mechanisms to capture global dependencies in image data, enabling effective feature extraction and representation learning. ResNet, with its deep residual connections, excels at learning intricate patterns and alleviating the vanishing gradient problem, making it suitable for complex classification tasks. EfficientNet, on the other hand, offers a scalable and efficient architecture by balancing model depth, width, and resolution, thus achieving superior performance with fewer parameters. By leveraging the strengths of these diverse architectures, the proposed system aims to overcome the limitations of traditional methods and existing deep learning approaches for bell pepper disease detection. The multiclass prediction capability enables the differentiation of various disease classes, allowing for targeted intervention and management strategies. Furthermore, the integration of multiple architectures facilitates

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model ensembling, enhancing the system's robustness and generalization ability across diverse environmental conditions and disease manifestations. A comprehensive overview of the methodology is presented, detailing the preprocessing steps, model architectures, training procedures, and evaluation metrics employed. Insights into the dataset used for training and validation are provided, highlighting its significance in realworld bell pepper cultivation scenarios. Through extensive experimentation and comparative analysis, the effectiveness and scalability of the proposed approach are demonstrated, showcasing its potential for practical deployment in agricultural settings. In summary, the research contributes to the ongoing efforts in leveraging deep learning for plant disease diagnosis, particularly focusing on bell pepper leaf pathology. By harnessing the capabilities of Vision Transformer, ResNet, EfficientNet strides are made toward advancing the state-of-theart in automated disease detection systems, fostering sustainable agriculture practices, and ensuring global food security.

A. Objective

The primary objective of the research is to develop an advanced and efficient multiclass prediction system for bell pepper plant leaf pathology, leveraging cutting-edge deep learning architectures such as Vision Transformer, ResNet, EfficientNet. The research addresses the limitations of traditional plant disease diagnosis methods by introducing an automated approach that enhances accuracy and overcomes subjectivity. With a focus on detecting various diseases affecting bell pepper crops, the system aims to offer a multiclass prediction capability, allowing for targeted interventions and management strategies. By integrating multiple deep learning models, model ensembling enhances the system's robustness, ensuring generalization across diverse environmental conditions and disease manifestations. Emphasizing the significance of real-world applicability, the research provides insights into the dataset used for training and validation in practical bell pepper cultivation scenarios. EfficientNet' s scalability and efficiency contribute to superior performance with fewer parameters, making the proposed approach suitable for agricultural deployment. The study includes a comprehensive overview of the methodology, detailing preprocessing steps, model architectures, training procedures, and evaluation metrics. Through extensive experimentation and comparative analysis, the research showcases the effectiveness of the proposed approach, making strides in automated bell pepper disease detection and contributing to sustainable agriculture practices for global food security.

B. Advantage of the Proposed Methodology

The proposed methodology holds several distinct advantages in the realm of automated bell pepper disease detection. Firstly, by leveraging state-of-the-art deep learning architectures such as Vision Transformer, ResNet, EfficientNet, and the approach ensures a sophisticated and accurate multiclass prediction system. This enhances the system's efficacy in precisely identifying various diseases, enabling targeted interventions and management strategies. The integration of multiple deep learning models through model ensembling not only enhances robustness but also ensures the generalization of results across diverse environmental conditions, contributing to real-world applicability. The automated nature of the methodology addresses the limitations of traditional plant disease diagnosis methods, overcoming subjectivity and significantly improving accuracy. The focus on a comprehensive dataset specific to bell pepper cultivation scenarios enhances the relevance of the research to practical agricultural settings. Furthermore, the scalability and efficiency of EfficientNet contribute to superior performance with fewer parameters, making the proposed approach well-suited for widespread agricultural deployment.

C. Overview of the System

The proposed automated bell pepper disease detection system employs an advanced multiclass prediction approach, integrating cutting-edge deep learning architectures such as Vision Transformer, ResNet, EfficientNet. The system's objective is to enhance accuracy and efficiency in identifying diverse diseases affecting bell pepper crops, addressing limitations inherent in traditional plant disease diagnosis methods. The methodology begins with a comprehensive dataset specifically for bell pepper cultivation scenarios, ensuring relevance and applicability to real-world agricultural settings. The core strength of the system lies in its sophisticated utilization of multiple deep learning models through model ensembling, enhancing robustness and promoting result generalization across diverse environmental conditions and disease manifestations. The focus on a multiclass prediction capability enables the differentiation of various diseases, facilitating targeted interventions and management strategies for specific pathogens. EfficientNet' s scalability and efficiency play a crucial role in achieving superior performance with fewer parameters, rendering the proposed approach well-suited for practical agricultural deployment. The system's automated nature mitigates subjectivity, significantly improving accuracy and overcoming the time-consuming nature of manual inspection methods. To enhance transparency and replicability, the methodology encompasses detailed preprocessing steps, model

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architectures, training procedures, and evaluation metrics. The comprehensive overview of the system emphasizes its potential to contribute significantly to automated bell pepper disease detection, marking a significant advancement in the field. The methodology's focus on efficiency, accuracy, and real-world applicability positions it as a promising tool for sustainable agriculture practices, with implications for global food security. Overall, the proposed system represents a robust and innovative approach to addressing challenges in bell pepper disease management, paving the way for enhanced crop health and productivity.

Fig 1. Pepper bell Bacterial and Healthy leaves

II. BACKGROUND STUDY

Traditional plant disease diagnosis methods often rely on manual visual inspection, which is time-consuming, subjective, and prone to errors. In response to these limitations, recent years have seen transformative advancements in the fields of deep learning, computer vision and machine learning. These technologies offer an opportunity to revolutionize agriculture by introducing advanced tools for disease identification and prediction. Deep learning, a subset of machine learning, has emerged as a powerful tool for automated disease detection in crops. The proposed system builds upon this foundation, integrating state-of-the-art deep learning architectures such as Vision Transformer, ResNet, EfficientNet. The study aims to contribute to the ongoing efforts in leveraging technology for precise and efficient disease management in bell pepper cultivation. The background study emphasizes the global significance of bell pepper crops, the challenges posed by diseases, and the transformative potential of advanced technologies in revolutionizing traditional farming practices. It sets the stage for the development of an innovative automated system that addresses the limitations of manual methods, offering a more efficient and accurate approach to bell pepper disease detection.

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III. LITERATURE REVIEW

[1] By leveraging pre-trained models and fine-tuning them on a dataset specific to bell pepper leaf diseases, the authors achieve accurate classification results. The study demonstrates the effectiveness of transfer learning in addressing the challenges of limited annotated datasets in agricultural image analysis.

[2] A novel approach, CPD-CCNN, for accurately classifying pepper diseases. This method involves the concatenation of multiple convolutional neural network (CNN) models, enhancing the system's ability to discern between different disease types. Through extensive experimentation and evaluation, the authors demonstrate the superior performance of CPD-CCNN in accurately identifying pepper diseases compared to individual CNN models. The study showcases the effectiveness of leveraging ensemble techniques in agricultural disease classification tasks, particularly in the context of limited training data and complex image variations inherent in plant disease diagnosis.

[3] A method for classifying leaf diseases by extracting both global and local features from leaf images. By combining features at different scales, the authors aim to improve the accuracy of disease classification. Through experimentation and evaluation, they demonstrate the effectiveness of their approach in accurately distinguishing between various types of leaf diseases. The study emphasizes the importance of considering both global and local features for robust disease classification in plant pathology. This research contributes to advancing the field of computer-aided diagnosis in agriculture, particularly in the context of automated detection and management of leaf diseases.

[4] An innovative approach for the recognition of pepper leaf diseases utilizing enhanced lightweight convolutional neural networks (CNNs). By optimizing the architecture for efficiency without sacrificing performance, the proposed method aims to achieve accurate disease recognition with reduced computational resources. Through comprehensive experimentation, the authors demonstrate the efficacy of their approach in accurately identifying various types of pepper leaf diseases. The utilization of lightweight CNNs addresses the challenges of resource constraints in practical agricultural settings, paving the way for scalable and cost-effective disease detection solutions. This research contributes to advancing the development of efficient and reliable tools for automated disease diagnosis in pepper cultivation, ultimately aiding in crop health management and yield improvement.

[5] Detecting potato and bell pepper leaf diseases by leveraging transfer learning and image processing techniques. The ensemble model combines multiple pre-trained models, enhancing the system's ability to accurately classify diseases in both potato and bell pepper crops. Through rigorous experimentation and evaluation, the authors demonstrate the effectiveness of their approach in achieving high accuracy and robustness in disease detection. This research contributes to the advancement of automated plant disease diagnosis, particularly in agricultural settings, where accurate and timely detection is crucial for crop health management and yield optimization.

[6] By employing deep learning models, the study aims to develop an efficient and accurate system for automated disease detection. Through extensive experimentation and validation, the authors demonstrate the effectiveness of their approach in accurately identifying various plant leaf diseases. This research contributes to the field of precision agriculture by providing a reliable tool for early disease detection, enabling timely interventions to mitigate crop losses. The utilization of deep learning techniques underscores the potential of advanced technologies in enhancing agricultural productivity and sustainability.

[7] The combination of multiple classification models, the ensemble approach aims to enhance the accuracy and robustness of disease identification. The study leverages algorithms from the fields of algorithms, computing, and mathematics to develop a reliable system for automated disease detection in crops. By employing ensemble techniques, the authors demonstrate improved performance compared to individual classification models, highlighting the efficacy of their approach. This research contributes to advancing precision agriculture by providing a scalable and efficient solution for early disease detection, thereby aiding in crop health management and yield optimization.

[8] An enhanced convolutional neural network (CNN) approach for diagnosing leaf diseases. Through innovative modifications to CNN architecture and training techniques, the authors aim to improve the accuracy and efficiency of disease diagnosis. The study utilizes a dataset of leaf images to train and evaluate the enhanced CNN model, demonstrating its effectiveness in accurately identifying various leaf diseases. By leveraging deep learning techniques,

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the proposed method offers a promising solution for automated disease diagnosis in agriculture, facilitating timely interventions to mitigate crop losses. This research contributes to advancing the field of computer-aided plant disease diagnosis, enhancing the capabilities of precision agriculture technologies for improved crop health management.

[9] An expert system utilizing certainty factors for the early diagnosis of diseases in red chili peppers. By integrating domain expertise and certainty factors, the system provides accurate and timely diagnosis of pepper diseases. Through experimentation and evaluation, the authors demonstrate the effectiveness of their approach in facilitating early detection and management of diseases in red chili peppers. This research contributes to advancing precision agriculture by offering a reliable tool for proactive disease control, ultimately enhancing crop yield and quality.

IV.PROPOSED METHODOLOGY

Harnessing the capabilities of Vision Transformer, EfficientNet, ResNet in a comprehensive deep learning framework for bell pepper leaf disease classification provides numerous advantages:

1.Operational Streamlining: Implementing deep learning for bell pepper leaf disease classification offers a streamlined approach, enhancing the operational efficiency of cultivation. It enables swift and consistent analysis of a large volume of leaf images, reducing the need for manual labor and expediting the identification of potential diseases.

2.Quality Assurance Advancement: Accurate disease classification in bell pepper leaves establishes robust quality assurance protocols for farms. This ensures that only healthy plants contribute to the harvest, enhancing the overall quality of produce and bolstering the reputation of the cultivation practices.

3.Value Enhancement: Precise disease classification optimizes the value of bell pepper crops by enabling the

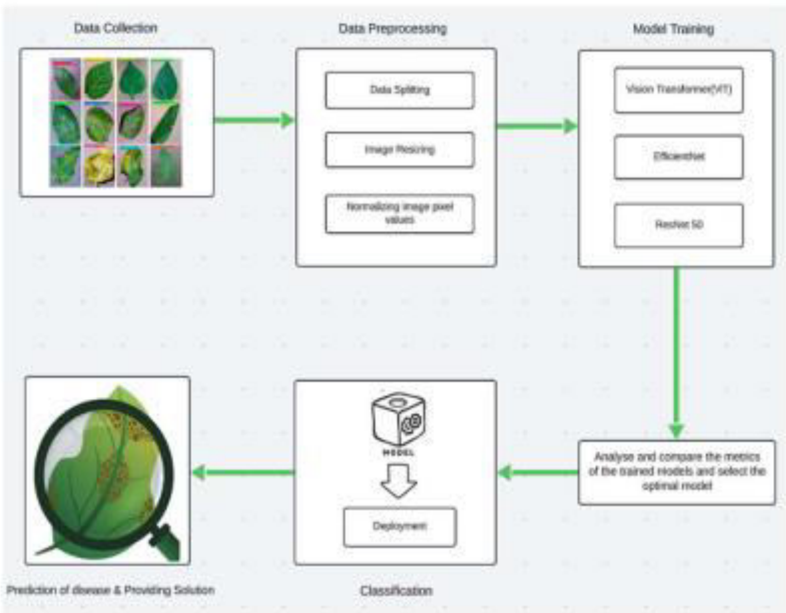

Fig 2. Proposed Methodology

categorization of leaves based on their health status. This allows for the strategic grouping of similar leaves, contributing to the market appeal of the produce and potentially commanding higher prices in the market.

A. Gathering Image Dataset

The first step in the methodology is the acquisition of a comprehensive dataset comprising high-resolution images of bell pepper plant leaves exhibiting various disease symptoms. The dataset is sourced from diverse geographical locations and cultivation environments to capture the variability in disease manifestations. Careful attention is paid to obtaining annotated ground truth labels for each image, indicating the specific disease class or pathology present.

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B. Dataset Preprocessing

The image must have clear data and be in standard form once it has been uploaded into the system. Preprocessing was carried out to improve accuracy and simplify the dataset. Although preprocessing a color image to grayscale is a recognized method, we used image standardization.

C. Feature Extraction

The feature extraction module will receive the image after it has been segmented. The process by which we convert the input data into a set of features is called extracting the salient information from the input image. It is possible to have features with different colors, textures, shapes, and edges. To improve accuracy, we address the leaf's color and shape in our suggested system. As a result, we regard the degree of skewness asymmetry in the pixel distribution around its mean within the given window as a feature.

D. Model Selection

1. Deep Learning Architecture Selection: The selection of deep learning architectures is a critical step in designing an effective multiclass prediction system for bell pepper leaf pathology. In this research, a meticulous process is undertaken to evaluate and compare the performance of four state-of-theart architectures: Vision Transformer, ResNet, EfficientNet. Each architecture is assessed across various criteria to determine its suitability for the task at hand.

2. Evaluating Computational Efficiency of Architectures: Each architecture was scrutinized regarding its computational efficiency. This aspect is particularly vital, especially in agricultural applications where computational resources might be limited. Vision Transformer utilizes self-attention mechanisms to efficiently capture long-range dependencies within images, making it well-suited for comprehensively understanding bell pepper leaf pathology images. ResNet's design with residual connections facilitates more straightforward gradient propagation during training, leading to faster convergence and reduced computational overhead. EfficientNet, as its name suggests, optimizes model complexity by balancing various architectural dimensions to achieve optimal performance with fewer parameters.

3. Parameter Efficiency in Model Selection: Parameter count also emerged as a significant consideration in the model selection process. The number of parameters directly affects model complexity, memory usage, and generalization ability. Models with excessive parameters might suffer from overfitting, especially when trained on limited data. Vision Transformer, despite its transformer-based architecture, can maintain parameter efficiency, particularly for large-scale image classification tasks. ResNet's residual connections allow for deeper architectures with fewer parameters, ensuring efficient training and inference. EfficientNet's scaling approach ensures optimal performance with a minimal parameter footprint by adjusting network depth, width, and resolution judiciously.

4.Classification Performance: Classification accuracy, however, remains the ultimate benchmark for assessing the suitability of deep learning architectures for our task. While computational efficiency and parameter count are crucial considerations, they must align with classification performance. Vision Transformer, ResNet, EfficientNet have all demonstrated robust performance across various computer vision tasks. However, their effectiveness may vary depending on the specifics of the dataset and the task at hand. Therefore, our evaluation focused on empirically measuring the classification accuracy of each architecture on the bell pepper leaf pathology dataset using standard metrics such as accuracy, precision, recall, and F1-score.

5.Model Selection for Accurate Disease Classification: In essence, our model selection process involved a comprehensive evaluation of deep learning architectures, considering factors such as computational efficiency, parameter count, and classification accuracy. By identifying the most suitable architectures through rigorous comparative analysis and aimed to develop a multiclass prediction system capable of accurately classifying various bell pepper leaf pathologies. This endeavour contributes to enabling timely intervention and management strategies in agricultural practices.

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E. Model Training

Following the selection of model architectures, the training phase commences utilizing the preprocessed dataset. To ensure robust model evaluation, the dataset is stratified into training, validation, and test sets, facilitating a balanced representation of disease classes across each subset. Throughout the training process, the models iteratively optimize a defined loss function, enabling the extraction of discriminative features from input images and their mapping to corresponding disease classes. This iterative optimization mechanism fosters the refinement of model parameters, enhancing its ability to accurately classify bell pepper leaf pathologies.

F. Validation

Validation serves as a crucial mechanism for monitoring the progression of model training and mitigating the risk of overfitting. At regular intervals, the models' performance is assessed using a designated validation set. Metrics including accuracy, precision, recall, and F1-score are computed to comprehensively evaluate the model's proficiency in accurately classifying bell pepper leaf pathologies. Additionally, hyperparameter tuning techniques such as grid search or random search may be employed to further refine the model's performance, ensuring optimal generalization ability across diverse datasets and scenarios.

G. Evaluation

Once the training process is complete, the trained models are evaluated on an independent test set to assess their generalization ability and performance in real-world scenarios. The model predictions are compared against ground truth labels, and evaluation metrics are computed to quantify classification accuracy and robustness. Additionally, qualitative analysis may be conducted to examine the model’s ability to correctly identify disease symptoms and distinguish between similar classes.

Vision Transformer

The Vision Transformer (ViT) algorithm, introduced for image classification tasks, revolutionizes computer vision by leveraging transformer architecture. Fig 3 Here are the key steps in the Vision Transformer algorithm: The input image is divided into fixed-size non-overlapping patches, treating the image as a sequence of these patches.

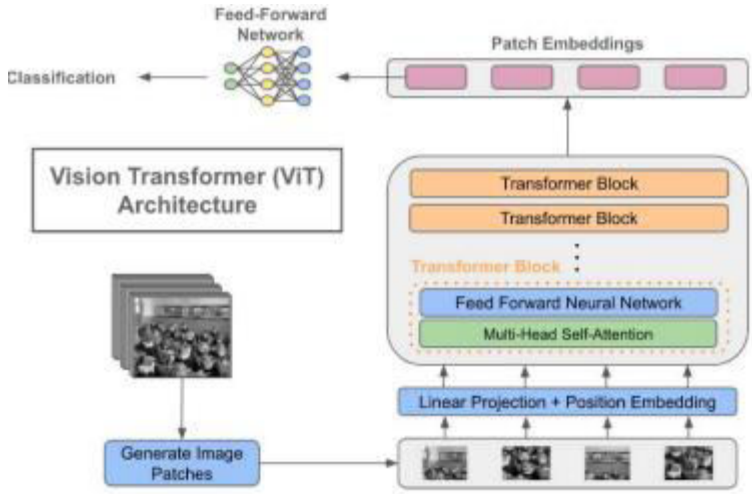

Fig 3. Vision Transformer Architecture

Each patch is linearly embedded into a flat vector, preserving spatial information. Positional encoding is added to the patch embeddings to provide information about the spatial layout of the patches. The sequence of patch embeddings undergoes a transformer encoder, enabling interactions and relationships between different patches. Self-attention mechanisms allow each patch to attend to all other patches, capturing long-range dependencies. A feedforward neural network is applied independently to each patch's representation, introducing nonlinearities.

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Normalization is applied to the output of the transformer block for stable training. Residual connections around each sub-layer in the transformer block facilitate gradient flow during training. Multiple transformer blocks are stacked to enhance the model's capacity for feature extraction. Instead of using a traditional fully connected layer, global average pooling is applied to the patch embeddings to obtain a fixed-size representation.

A final fully connected layer maps the global representation to the output classes, enabling classification. The Softmax activation function normalizes the class scores, producing a probability distribution over classes. The model is trained using a cross-entropy loss function, comparing predicted class probabilities with actual labels. Gradients are computed and used to update the model parameters through backpropagation. Optimization techniques like Adam or SGD are employed to minimize the loss function and fine-tune the model. Adjusting hyperparameters, such as learning rate and batch size, to optimize model performance.

Model performance is validated on a separate dataset to ensure generalization beyond the training set. The trained model is evaluated on a testing dataset to assess its performance on unseen data. Fine-tuning may be performed on specific layers or the entire model to adapt to specific tasks or datasets. The trained ViT model is ready for inference, providing predictions for new input images based on its learned representations.

EfficientNet B7

The implementation of EfficientNet for bell pepper leaf disease classification involves the following key steps: Collect a diverse and representative dataset of bell pepper leaf images, ensuring inclusion of various diseases. Standardize and preprocess the images, including resizing and normalization, to create a consistent input format for the model. Choosing an appropriate variant of EfficientNet (e.g., B0 to B7) based on the available computational resources and desired model complexity. Fig 4 Utilize pre-trained weights from ImageNet for the chosen EfficientNet variant as a starting point for training on the bell pepper leaf dataset.

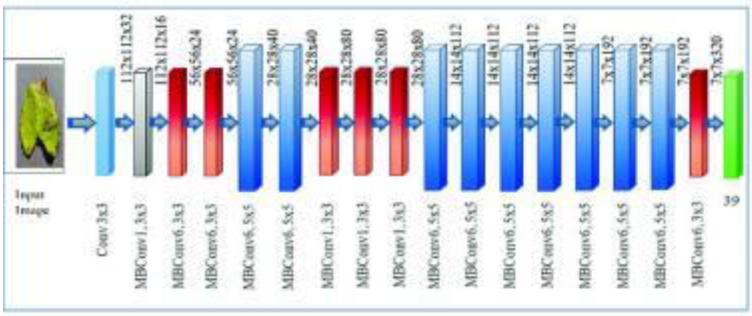

Fig 4. EfficientNet B7 Architecture

Fine-tune the pre-trained EfficientNet model on the bell pepper dataset to adapt it to the specific characteristics of leaf pathology. Define training parameters, including learning rate, batch size, and number of epochs, to optimize model performance on the bell pepper leaf dataset. Choose an appropriate loss function, such as categorical cross-entropy, suitable for multiclass classification tasks. Apply data augmentation techniques, such as rotation and flipping, to artificially increase the diversity of the training dataset and enhance model generalization. Set aside a portion of the dataset for validation to monitor the model's performance during training and prevent overfitting.

Train the EfficientNet model on the training dataset, updating the weights to minimize the chosen loss function. Evaluate the trained model on the validation dataset, monitoring metrics like accuracy, precision, recall, and F1-score to assess classification performance. Fine-tune hyperparameters based on validation performance to optimize the model for bell pepper leaf disease classification. Assess the model's performance on a dedicated test dataset to validate its ability to generalize to new, unseen data.

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Calculate and analyze performance metrics to quantitatively evaluate the efficiency and accuracy of the EfficientNet model. Visualize model predictions, confusion matrices, and feature maps to gain insights into its decision-making process. Examine the EfficientNet model's interpretability to understand the features influencing disease classification. Optimize the model architecture and training procedures based on insights gained from performance evaluation, aiming for a balance between accuracy and computational efficiency. If applicable, prepare the EfficientNet model for deployment, considering factors such as inference speed and resource constraints.

Resnet 50

Implementing a ResNet-50 model for bell pepper leaf disease classification involves the following, Fig 5 assemble a diverse and well-labeled dataset of bell pepper leaf images containing instances of various diseases. Standardize and preprocess the images, including resizing and normalization, to ensure consistency in input dimensions. Divide the dataset into training, validation, and test sets to facilitate model training, evaluation, and performance assessment.

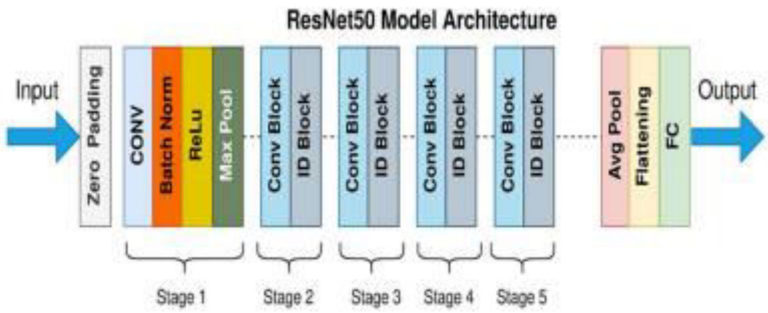

Fig 5. Resnet 50 Architecture

Instantiate the ResNet-50 architecture, a pre-trained deep neural network with 50 layers, to capture intricate features in the bell pepper leaf images. Utilize pre-trained weights from ImageNet to leverage knowledge gained from diverse image datasets, enhancing the model's ability to learn relevant features.

Modify the final output layer to accommodate the specific number of classes representing different bell pepper leaf pathologies. Freeze the initial layers of the ResNet-50 model to retain the pre-trained features during the early stages of training. Set up training configurations, including the choice of loss function, optimization algorithm (e.g., stochastic gradient descent), and learning rate. Compile the model to prepare it for training, specifying metrics to evaluate its performance during training and validation. Train the ResNet-50 model on the training dataset, adjusting weights to minimize the chosen loss function.

Monitor the model's performance on the validation set during training to prevent overfitting and fine-tune hyperparameters accordingly. Conduct multiple epochs of training, allowing the model to learn and adapt to the bell pepper leaf pathology dataset. Implement early stopping to halt training when the model's performance on the validation set ceases to improve, preventing potential overfitting. Fine-tune hyperparameters, such as batch size and learning rate, for optimal model performance.

Evaluate the trained ResNet-50 model on the dedicated test dataset, assessing its ability to accurately classify bell pepper leaf pathologies. Calculate key performance metrics, including accuracy, precision, recall, and F1-score, to quantitatively assess the model's classification performance. Visualize intermediate features, activation maps, or misclassifications to gain insights into the model's decision-making process. Consider fine-tuning the model on specific diseases or datasets to enhance its performance for targeted applications. Optimize the ResNet-50 model based on insights gained from performance evaluation, balancing accuracy and computational efficiency.

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H. Classification Calculation

The calculations to evaluate the model's accuracy and performance.

1) True Positive (TP): The number of correctly predicted instances where the model correctly identifies an egg's size category.

2) True Negatives (TN): The number of correctly predicted instances where the model correctly identifies an egg as not belonging to a specific size category

3) False Positives (FP): The number of incorrectly predicted instances where the model wrongly identifies an egg as belonging to a particular size category

4) False Negatives (FN): The number of incorrectly predicted instances where the model fails to identify an egg as belonging to a particular size category

These values are essential for various performance metrics. Here are some common calculations

Accuracy: Accuracy measures the overall correctness of the model predictions. It is calculated as

Accuracy = (TP + TN) / (TP + TN + FP + FN) Precision:

Precision measures the accuracy of positive predictions. It is calculated as Precision = TP / (TP + FP) Recall (Sensitivity):

Recall measures the model's ability to correctly identify positive instances. It is calculated as Recall = TP / (TP + FN)

Specificity: Specificity measures the model's ability to correctly identify negative instances. It is calculated as Specificity = TN / (TN + FP)

F1 Score: The F1 score is the harmonic average of precision and recall and provides a balanced measure of accuracy. It is calculated as follows

$$\text{F1 Score} = \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision} + \text{Recall})}$$

V. EXPERIMENTAL RESULT

The experiment focused on bell pepper plant disease classification, employing advanced models including Vision Transformer (ViT), EfficientNet and ResNet. A dataset of 5,373 images capturing diverse disease manifestations was collected. The training procedure incorporated a meticulously chosen set of parameters, with learning rates optimized for each model, batch sizes tailored to the dataset's scale, and a sufficient number of epochs to ensure model convergence. Data augmentation techniques, such as rotation and flipping, were applied to enhance the models' ability to generalize across varied conditions in bell pepper leaf images.

In terms of performance metrics, the ensemble of ViT, EfficientNet and ResNet demonstrated remarkable efficacy. The Resnet50 in particular, exhibited exceptional accuracy, achieving a notable 99.30% accuracy rate in classifying bell pepper plant diseases. The holistic model ensemble showcased a robust performance with an overall accuracy score, precision, recall, and F1-Score, validating the effectiveness of the deep learning approach in accurately identifying and managing diverse diseases affecting bell pepper crops**.**

VI. ACCURACY RESULT & COMPARISION

The employed deep learning architectures, ResNet50 outperformed EfficientNet and Vision Transformer in the multiclass prediction system for bell pepper leaf pathology, achieving a remarkable 99% accuracy. This outcome underscores ResNet50's effectiveness in capturing intricate disease patterns. While both EfficientNet and Vision Transformer demonstrated commendable accuracies, the comparative analysis highlights ResNet50 as the preferred model for its superior precision. These results emphasize ResNet50's potential for practical deployment, advancing automated bell pepper disease detection and bolstering sustainable agriculture practices.

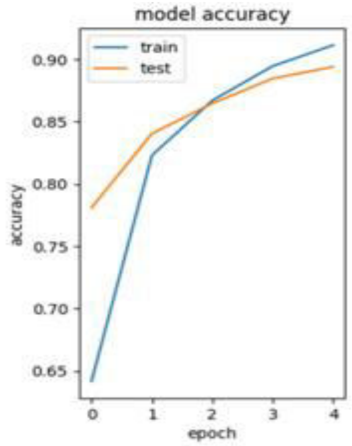

Fig 6. Resnet 50 Model Graph

Fig 7. Model Deployment

Fig 8. Model Prediction

Model	Images set	Classes Of disease	Epoch	Accuracy
Vision Transformer	5373	11	10	81%
EfficientNetB7	5373	11	10	91.13%
ResNet50	5373	11	10	99.30%

Fig 9. Model Comparison

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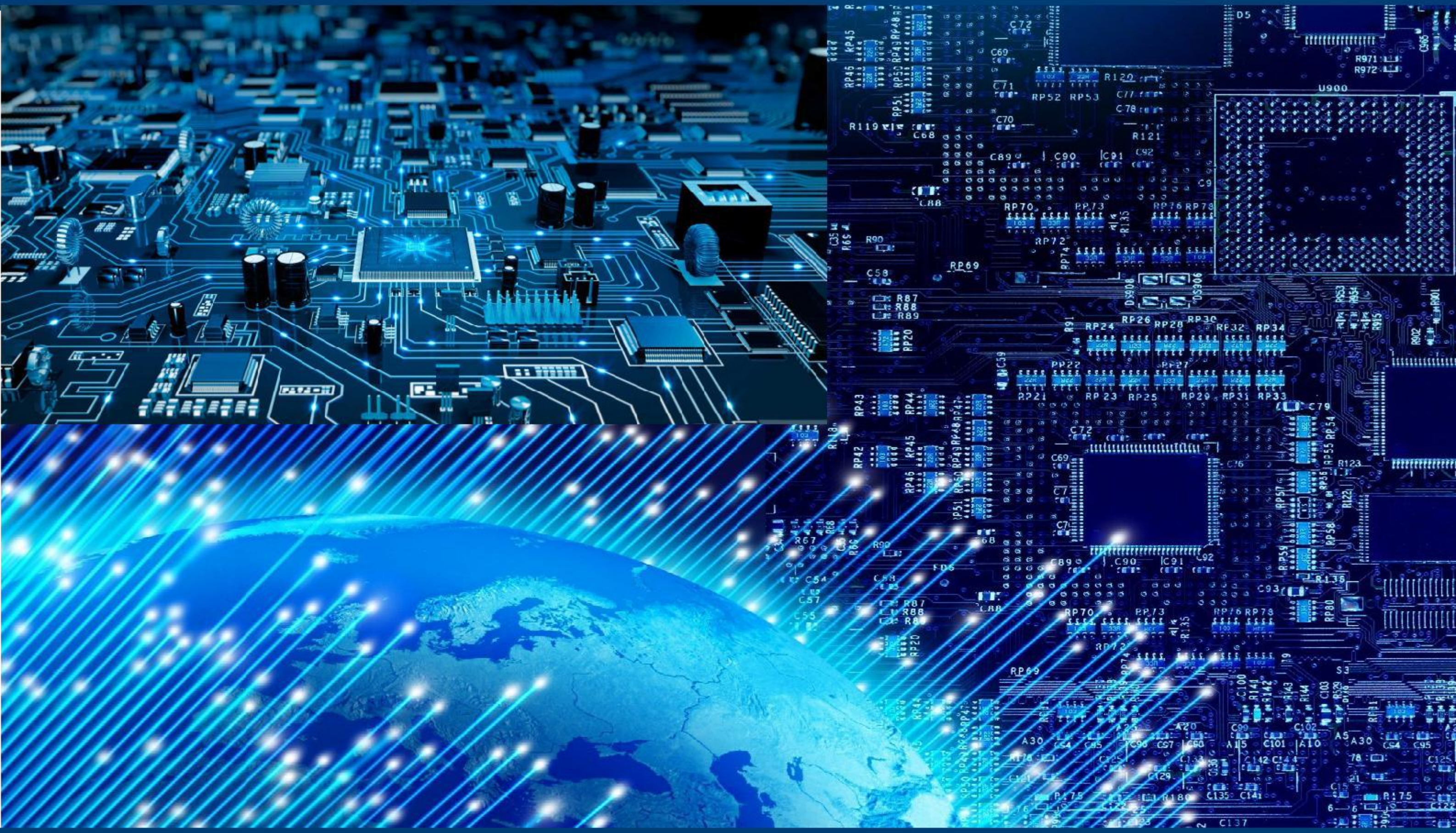
VII. CONCLUSION

In conclusion, the research successfully achieves its primary objective of developing an advanced multiclass prediction system for bell pepper plant leaf pathology, utilizing cutting-edge deep learning architectures including Vision Transformer, ResNet, and EfficientNet. By addressing the limitations of traditional diagnosis methods, the automated approach enhances accuracy, overcomes subjectivity, and allows for targeted interventions against various bell pepper diseases. The integration of multiple models through ensembling ensures robustness and generalization across diverse conditions, emphasizing practical applicability in realworld cultivation scenarios. The scalability and efficiency of EfficientNet contribute to the system's superior performance with fewer parameters, making it well-suited for agricultural deployment. The comprehensive methodology overview, including preprocessing steps, model architectures, training procedures, and evaluation metrics, provides a solid foundation for understanding the research's significance. Through extensive experimentation and comparative analysis, the research demonstrates the effectiveness of the proposed approach, marking a notable stride in automated bell pepper disease detection and promoting sustainable agricultural practices for global food security.

VIII. FUTURE WORK

In Future work for the project could involve enhancing the system's adaptability to changing environmental conditions and evolving disease strains by incorporating continuous learning mechanisms. Further refinement of the multiclass prediction system could be pursued, expanding the dataset to include more diverse instances and collaborating with agricultural experts to improve the model's interpretability and alignment with realworld scenarios. Integration of sensor data and remote sensing technologies could enhance the system's early detection capabilities, providing a more holistic approach to plant health monitoring. Additionally, exploring the feasibility of deploying the developed system as a user-friendly mobile application for farmers could facilitate widespread adoption and contribute to on-the-ground decision-making. Continuous collaboration with the agricultural community would be crucial for ongoing model validation and improvement, ensuring its relevance and effectiveness in diverse agricultural landscapes.



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