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Advanced CNN Technique for Plant Health Monitoring: Drop Path, SE Block and Efficient Scaling

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Abstract*: -* The early detection of plant diseases is crucial for improving agricultural productivity, and convolutional neural networks (CNNs) have emerged as a leading tool for this task. Recent advancements in CNN architectures, such as the incorporation of DropPath and Squeeze-and-Excitation (SE) blocks, have significantly improved disease classification accuracy. The DropPath technique enhances model generalization by preventing overfitting, allowing CNNs to better adapt to diverse agricultural datasets. Additionally, the SE block refines feature extraction by adaptively recalibrating channel-wise feature responses, enabling the model to focus on important characteristics of plant leaves and suppressing irrelevant ones. These innovations increase the model's ability to distinguish between healthy and diseased leaves, making it more effective in real-world agricultural applications. When combined with compound scaling, these techniques reduce computational costs while enhancing performance. Hybrid models that integrate CNNs with other machine learning methods further improve disease detection. Overall, these advancements in CNN architecture provide efficient, scalable, and accurate solutions for plant health monitoring, ensuring timely interventions and minimizing crop losses due to diseases.

Keywords: CNN, Compound scaling, Deep learning, DropPath.

I. INTRODUCTION

Early detection of plant diseases is essential for ensuring food security and improving agricultural productivity. Traditional methods of plant disease identification, such as manual inspection and laboratory analysis, are often time-consuming, labour-intensive, and susceptible to human error. With the advent of deep learning, convolutional neural networks (CNNs) have emerged as a powerful tool for automating plant disease detection through image-based analysis. These models have demonstrated remarkable success in identifying healthy and unhealthy leaves with high accuracy [1]. Studies have shown that CNNs can effectively classify plant diseases using image-based analysis [2]. Additionally, deep learning approaches have outperformed traditional methods in terms of accuracy and efficiency [3].

Recent advancements in CNN architectures have further enhanced their effectiveness in plant disease classification. Techniques such as DropPath regularization and Squeeze-and-Excitation (SE) blocks have been integrated into CNN models to improve generalization and feature extraction. DropPath mitigates overfitting by randomly disabling certain network pathways during training, enabling the model to learn more robust representations. Meanwhile, SE blocks refine feature extraction by dynamically recalibrating channel-wise feature responses, allowing the model to focus on the most relevant characteristics of plant leaves [4].

Moreover, the incorporation of compound scaling techniques has proven to be instrumental in optimizing CNN models for plant disease detection. Compound scaling enhances model performance by uniformly scaling network depth, width, and resolution, thereby reducing computational costs while maintaining high classification accuracy [5]. This study explores the impact of these innovations on CNN-based plant disease detection, highlighting their advantages in scalability, efficiency, and real-world applicability. By leveraging state-of-the-art CNN techniques, agricultural stakeholders can achieve timely disease identification, leading to proactive intervention and reduced crop losses.

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II. RELATED WORK

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized plant disease detection, providing higher accuracy and automation compared to conventional methods. Traditional approaches, such as manual visual inspection and biochemical testing, are often subjective, time-consuming, and require specialized expertise, making them impractical for large-scale agricultural applications. Machine learning and deep learning techniques have addressed these limitations by enabling automated, efficient, and reliable plant disease identification [6]. Among these, CNNs have emerged as the most effective due to their ability to automatically learn complex hierarchical patterns from leaf images, reducing the dependency on handcrafted features. Unlike classical machine learning models such as Support Vector Machines (SVMs) and decision trees, CNNs excel in extracting spatial and structural patterns from images, leading to more robust and generalized disease classification across different plant species [7]. Furthermore, CNN-based models have been successfully deployed to detect various plant diseases, demonstrating superior performance over traditional classifiers in terms of accuracy and scalability [8].

Recent advancements in CNN architectures have further refined plant disease detection models, incorporating novel techniques to optimize performance and efficiency. One significant innovation is compound scaling, which systematically balances the depth, width, and resolution of CNNs, ensuring enhanced feature extraction and improved classification accuracy [9]. Additionally, architectural enhancements such as Squeeze-and-Excitation (SE) blocks have been introduced to refine channel-wise feature recalibration, allowing models to focus on crucial leaf characteristics while suppressing irrelevant information. DropPath regularization has also been integrated into CNN frameworks to mitigate overfitting and enhance model generalization when applied to diverse agricultural datasets [10]. Furthermore, hybrid models that combine CNNs with other machine learning techniques, such as SVMs, Recurrent Neural Networks (RNNs), and Attention-based mechanisms, have demonstrated superior classification accuracy by leveraging the strengths of multiple learning paradigms [11]. Optimization techniques, including extensive data augmentation, transfer learning from large-scale datasets, and fine-tuning of pre-trained CNN architectures like EfficientNet and ResNet, have further improved CNN performance in plant disease detection tasks [12].

Efforts to enhance computational efficiency and accessibility have led to the development of lightweight CNN architectures and model compression techniques, including quantization and pruning, which significantly reduce computational costs while maintaining high classification accuracy [13]. These advancements have enabled real-time plant disease identification through mobile applications and cloud-based platforms, allowing farmers and agricultural professionals to detect diseases using smartphone cameras, receive instant feedback, and take timely corrective measures [14]. Furthermore, emerging technologies such as the Internet of Things (IoT) and edge computing are being integrated with CNN-based models to facilitate continuous crop health monitoring, enabling precision agriculture solutions that ensure early disease intervention. Future research aims to expand agricultural datasets to include diverse plant species, environmental variations, and disease conditions, further improving the robustness and applicability of CNN-based models in practical agricultural settings [15].

The effects of compound scaling on CNN performance in agricultural applications have been analysed, demonstrating that adjusting the depth, width, and resolution of a CNN simultaneously improves both accuracy and efficiency [16]. This technique enhances model robustness and adaptability to diverse plant datasets while reducing computational costs. The findings indicate that CNNs with compound scaling outperform traditional scaling methods, making them more effective for real-world agricultural use.

A novel CNN-based approach for plant leaf disease detection has also been proposed, emphasizing the importance of optimizing CNN architecture for agricultural datasets [17]. By incorporating enhanced feature extraction techniques tailored for different plant diseases, the model achieves improved classification accuracy. A well-optimized CNN significantly outperforms conventional machine learning methods in plant disease detection, demonstrating the advantages of specialized CNN architectures.

III. METHODOLOGY

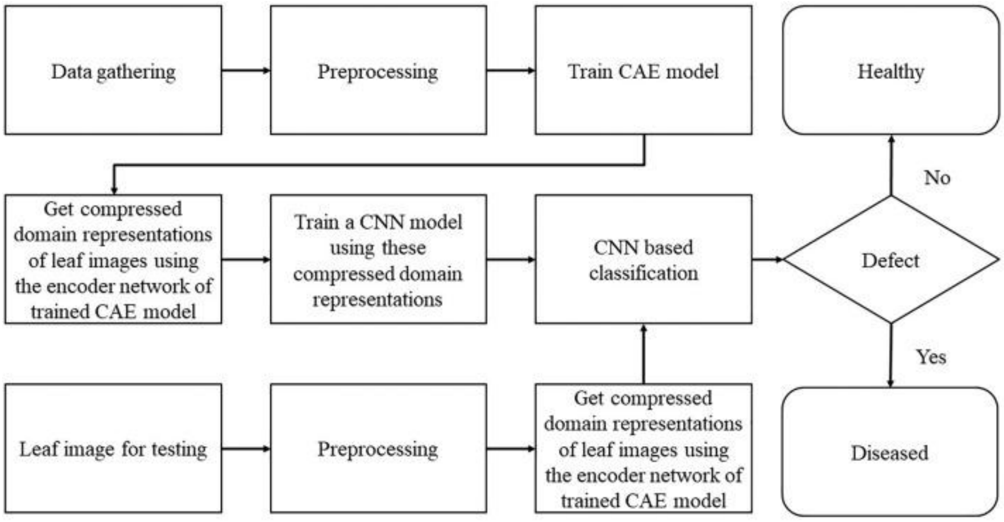

Figure 1: Block Diagram of CNN [18]

The block diagram represents a hybrid plant disease detection model that combines a Convolutional Auto encoder (CAE) and a Convolutional Neural Network (CNN) to classify plant leaves as either healthy or diseased [18]. The process begins with data gathering, where leaf images are collected from agricultural datasets or real-world sources for both training and testing. The collected images undergo pre-processing, which includes resizing, normalization, and noise removal to enhance image quality before feature extraction.

Once pre-processing is complete, a CAE model is trained to learn compressed feature representations of leaf images. The encoder part of the CAE extracts meaningful features while reducing dimensionality, ensuring that only the most relevant information is retained. These compressed domain representations of leaf images, generated using the trained CAE encoder, serve as inputs for the CNN model. Instead of using raw images, the CNN is trained on these extracted features, allowing it to classify plant diseases more effectively while reducing computational complexity.

For testing, a new leaf image is first pre-processed and then passed through the trained CAE encoder, which extracts its compressed feature representation. This feature representation is then fed into the CNN-based classification module, which determines whether the leaf is healthy or defective. If the model does not detect any defects, the leaf is classified as healthy. However, if a defect is detected, the process moves to the next stage, where the leaf is classified as diseased.

This hybrid approach offers multiple advantages. By utilizing a CAE, the model effectively reduces dimensionality, improving computational efficiency without losing essential features. The CNN, trained on these compressed representations, achieves higher classification accuracy while minimizing overfitting. The integration of both models ensures better generalization and scalability, making the system well-suited for real-world agricultural applications. Overall, this methodology provides an efficient, accurate, and scalable solution for plant disease detection, facilitating early identification and helping prevent significant crop losses [18].

DropPath Theory and Its Role in CNNs

DropPath is an advanced **regularization technique** used in deep learning, particularly in **Convolutional Neural Networks (CNNs)**, to **improve generalization and prevent overfitting**. Unlike traditional **Dropout**, which randomly removes individual neurons, DropPath **randomly disables entire computational paths** during training. This means that in each forward pass, different subnetworks are trained, forcing the model to learn a more diverse set of feature representations rather than relying on specific pathways **[19]**. This approach significantly enhances model robustness and adaptability, making it well-suited for **plant disease detection and classification tasks**.

In CNN-based plant health monitoring, **DropPath plays a crucial role in enhancing model performance**. It has been particularly effective in **deep architectures with residual connections**, such as **ResNet, EfficientNet, and Transformer-based models**. Since these architectures rely on multiple paths of information flow, DropPath ensures that no single path dominates the learning process. By randomly deactivating different computational paths at different training steps, DropPath compels the model to explore multiple representations of plant features, leading to improved

feature diversity and robustness [19].

A significant application of DropPath is in **compound scaling approaches**, where depth, width, and resolution adjustments are made simultaneously to optimize CNN performance. Research has shown that **combining DropPath with compound scaling** ensures that feature learning is well-distributed across different layers of the network, resulting in better generalization and **higher classification accuracy in plant disease detection [20]**. This is particularly beneficial in agricultural datasets, where variations in lighting, leaf angles, and environmental noise can affect classification performance. By making CNNs more resilient to these variations, DropPath improves their **reliability in real-world applications**.

Moreover, DropPath has been successfully integrated into **hybrid models**, such as those combining CNNs with **Adaptive Neuro-Fuzzy Inference Systems (ANFIS)**, to improve classification efficiency. These hybrid architectures leverage **fuzzy logic** for better interpretability while using CNNs for feature extraction. The **incorporation of DropPath in ANFIS-based CNNs** has been shown to reduce **overfitting**, ensuring that models generalize well across different plant species and disease types **[21]**. This is especially important in large-scale agricultural applications, where models need to perform consistently across diverse datasets.

Furthermore, comparative studies on **different CNN architectures for leaf disease detection** have demonstrated that **DropPath-enhanced models outperform traditional models**. By improving generalization, reducing **model overfitting**, and increasing classification accuracy, DropPath has become an essential tool in **CNN-based plant health monitoring [22]**.

In conclusion, DropPath is a **powerful regularization technique** that significantly enhances CNN-based models for **plant disease detection**. By preventing overfitting, encouraging diverse feature learning, and improving **model stability and accuracy**, DropPath ensures that CNNs can effectively classify plant diseases under varying environmental conditions

Advancement in CNN: The rapid advancements in **Convolutional Neural Networks (CNNs)** have significantly improved the ability to detect and classify plant diseases using leaf images. Researchers have focused on enhancing CNN architectures to improve **feature extraction, classification accuracy, computational efficiency, and generalization** across diverse plant species. Recent studies have explored **Dense CNNs, lightweight architectures, early detection methods, and tensor-based learning techniques**, all of which contribute to the growing effectiveness of deep learning in agricultural disease detection.

1. Multi-Class Plant Disease Detection Using Dense CNNs

One of the major challenges in plant disease detection is the ability to **distinguish multiple plant diseases** from leaf images with high accuracy. A study utilizing **Dense Convolutional Neural Networks (Dense-CNNs)** demonstrated that **densely connected layers** improve feature propagation, mitigate the vanishing gradient problem, and encourage **feature reuse** across layers. This architecture is particularly effective in **multi-class classification tasks**, where diseases exhibit **similar visual symptoms** such as yellowing, spotting, and necrosis **[23]**.

Dense-CNNs have been shown to perform well when trained on large-scale datasets containing images of leaves affected by **various fungal, bacterial, and viral infections**. Unlike traditional CNNs, which rely on sequential feature extraction, Dense-CNNs ensure that each layer has direct access to all preceding layers, leading to **better information flow and more robust feature representation**. This approach enables **highly efficient feature extraction**, ensuring that even minor variations in plant leaf conditions are accurately detected **[23]**.

2. Survey on Deep CNNs for Plant Disease Prediction

Another study conducted a comprehensive **survey on deep CNN architectures** for plant disease detection, comparing models such as **ResNet, EfficientNet, MobileNet, and VGGNet**. The research found that while **deeper CNN architectures** like ResNet and EfficientNet provide high accuracy, they require substantial computational resources, making them less suitable for real-time agricultural applications. On the other hand, **lightweight CNN architectures like MobileNet** offer a balance between **accuracy and efficiency**, making them ideal for **on-field disease monitoring using mobile and edge devices [24]**. The study also highlighted that **incorporating attention mechanisms, feature refinement techniques, and advanced activation functions** can significantly improve CNN performance. Techniques such as **Squeeze-and-Excitation (SE) blocks** and **DropPath regularization** were identified as key contributors to enhancing model generalization and reducing overfitting in plant disease classification tasks **[24]**. These findings underscore the importance of selecting an **optimal CNN architecture based on the computational constraints and deployment requirements** in agricultural settings.

3. Early Detection of Plant Diseases Using Low-Resolution Images

Timely detection of plant diseases is crucial for **preventing crop losses and improving agricultural yield**. A study on the early detection of **coffee leaf rust** explored the use of **CNNs trained on low-resolution images** to identify diseases at their **incipient stages**. The results demonstrated that **deep learning models can accurately classify early-stage infections**, even when image quality is low **[25]**.

This study is particularly significant for **small-scale farmers** and **regions with limited technological resources**, where high-resolution imaging devices may not be readily available. The ability of CNNs to extract meaningful features from **low-quality images** suggests that plant disease detection systems can be deployed using **basic smartphones and low-cost cameras** without compromising accuracy. Additionally, the research found that **pretrained CNNs with transfer learning** improved early detection rates, making deep learning models more adaptable to different agricultural datasets **[25]**.

4. Enhancing Plant Disease Detection with Tensor Subspace Learning and HOSVD-MD

Beyond traditional CNN architectures, researchers have explored the integration of **tensor-based learning techniques** to further enhance plant disease classification. A novel study introduced a CNN model combined with **Higher-Order Singular Value Decomposition (HOSVD) and Tensor Subspace Learning**, which aims to **reduce feature redundancy and improve classification robustness [26]**.

This method provides several advantages:

- **Efficient Feature Representation**: Tensor-based learning methods help CNNs **capture complex relationships between different features**, ensuring that subtle variations in plant diseases are effectively identified.
- **Improved Model Generalization**: By reducing **unnecessary features**, this technique ensures that CNNs do not overfit to specific datasets but rather learn **general patterns of disease symptoms**, improving real-world applicability.
- **Better Handling of High-Dimensional Data**: Plant disease datasets often contain **thousands of leaf images with different environmental conditions**. The **HOSVD-MD approach** compresses these high-dimensional features, making computations **faster and more efficient** while maintaining accuracy **[26]**.

This study demonstrates that combining **traditional deep learning methods with tensor-based optimization techniques** significantly enhances plant disease detection models, making them **more scalable and adaptable to large agricultural datasets**. These advancements underscore the growing potential **of CNNs as scalable, efficient, and practical tools for plant health monitoring** in modern agriculture. Future research directions could focus on **real-time disease detection using IoT devices, integration with hyperspectral imaging, and hybrid deep learning models incorporating attention mechanisms and fuzzy logic.** By continuing to refine CNN architectures and optimization techniques, deep learning models can play an increasingly crucial role in **ensuring early disease intervention and improving global agricultural productivity**

Methodology

DropPath (also called stochastic depth) is a regularization technique used in deep neural networks where entire residual blocks are randomly dropped during training. This encourages feature diversity and prevents overfitting, similar to Dropout, but applied to residual connections instead of individual neurons.

In a standard residual block, we have:

$x$out = $F(x) + x$

where: x is the input to the residual block and $F(x)$ is the transformation applied by the block. The residual connection ensures better gradient flow.

With DropPath, the residual connection is randomly dropped with probability 1−p1 -
p1−p, so during training:

$x$out = $F(x) + x$, $with\ probability\ p$ **or**

$x\text{out} = F(x)$, $with\ probability\ (1 - p)$

To maintain expected values in inference mode, we scale by p during training:

$x\text{out} = x + pF(x)$

Mathematical Formulation

Let:

- x be the input tensor.
- $F(x)$ be the residual block transformation.
- B be a Bernoulli random variable with probability p

Then:

- $B \sim \text{Bernoulli}(p)$

$x\text{out} = x + B \cdot F(x)$

During inference, we apply:

$x\text{out} = x + p \cdot F(x)$

which ensures that the expected output remains the same.

2. Modified Squeeze-and-Excitation (SE) Block – Theory & Math

A Squeeze-and-Excitation (SE) block improves channel-wise feature recalibration by learning channel dependencies. It does so using two main steps:

1. Squeeze (Global Information Embedding)
   - Compute a global average pooling (GAP) across spatial dimensions.
   - Output a global descriptor for each channel.
2. Excitation (Channel Attention)
   - Pass the squeezed features through a small MLP (two FC layers) with a non-linearity.
   - Apply Sigmoid activation to obtain attention weights.
   - Reweight the original feature maps by these learned weights.

A modified SE block can:

1. Use different non-linearities (e.g., SiLU instead of ReLU).
2. Modify pooling operations (e.g., max pooling + avg pooling).
3. Change the attention mechanism (e.g. use softmax instead of sigmoid)

Figure 2: Dataset

Image no 2 shown are part of a dataset consisting of 500 samples used for detecting healthy and unhealthy **Chitrak (Plumbago) plant leaves** through a **Convolutional Neural Network (CNN).** Each image serves as input for training a model to classify leaf health based on visible features such as discoloration, spots, or texture changes. Healthy leaves appear uniform in color and structure, while unhealthy leaves may show signs of disease, nutrient deficiency, or physical damage. These images undergo pre-processing techniques such as resizing, normalization, and data augmentation to improve the model's accuracy and generalization. By analysing these images, the system aims to enhance early disease detection and support precision agriculture.

IV. RESULT

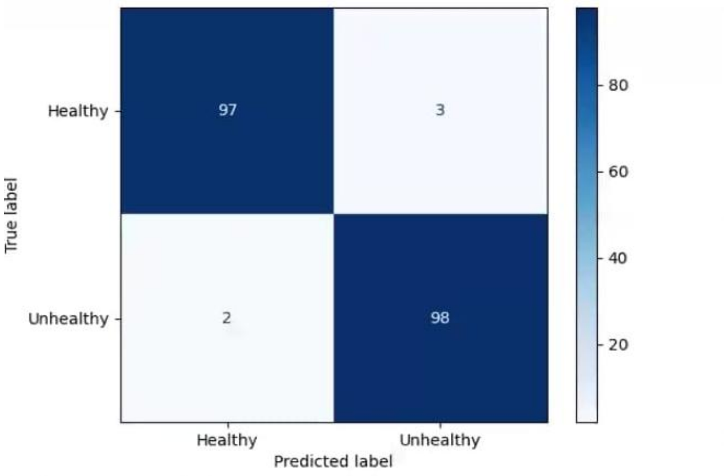

Figure 3: Confusion Matrix

The Figure represents a confusion matrix, which is a performance evaluation tool used in machine learning classification tasks. It provides a detailed breakdown of how well a model performs by comparing its predictions with actual ground truth labels. The matrix consists of four quadrants, each representing different classification outcomes.

In this case, the model is classifying data into two categories: Healthy and Unhealthy. The rows represent the actual (true) labels, while the columns represent the predicted labels. The numbers inside the matrix indicate the number of cases that fall into each category.

- True Positives (Bottom Right: 98): These are cases where the actual label was Unhealthy, and the model correctly predicted them as Unhealthy.
- True Negatives (Top Left: 97): These are cases where the actual label was Healthy, and the model correctly predicted them as Healthy.
- False Positives (Top Right: 3): These are cases where the actual label was Healthy, but the model incorrectly predicted them as Unhealthy. This is also known as a Type I error.

- False Negatives (Bottom Left: 2): These are cases where the actual label was Unhealthy, but the model incorrectly predicted them as Healthy. This is also called a Type II error.

The performance of the classification model can be evaluated using key metrics derived from the confusion matrix**. Accuracy,** which measures the proportion of correctly classified instances out of the total cases, is calculated as the sum of true positives and true negatives divided by the total number of predictions. In this case, the model achieves an impressive accuracy of **97.5%,** meaning it correctly classifies the vast majority of cases. Another important metric is **precision,** which indicates how many of the predicted "Unhealthy" cases were actually unhealthy. With a precision of **97.03%,** the model demonstrates that it makes very few false positive predictions, meaning it does not frequently misclassify healthy individuals as unhealthy. Furthermore**, recall**, also known as sensitivity, measures how well the model identifies actual unhealthy cases. The recall value of **98%** suggests that the model successfully detects nearly all unhealthy individuals, with only a small number of false negatives. This high recall score indicates that the model is reliable in identifying unhealthy cases, which is particularly important in medical or diagnostic applications where missing a true unhealthy case could have serious consequences. The low number of **false positives (3)** and **false negatives (2)** further supports the model's reliability, as it makes very few misclassifications overall. Overall, the model demonstrates **exceptional performance,** with high accuracy, precision, and recall. Its ability to correctly classify both healthy and unhealthy individuals with minimal errors makes it a robust and effective tool for classification tasks in healthcare or similar domains.

The given Figure no 4 contains two graphs that illustrate the training and validation loss (left) and training and validation accuracy (right) over multiple epochs. These graphs help assess how well the model is learning and whether it is generalizing effectively to unseen data. In the left graph, the training loss, represented by the blue line, decreases steadily over time, indicating that the model is learning patterns from the training data effectively. However, the validation loss, shown in orange, fluctuates significantly instead of following the same downward trend. It exhibits sharp spikes and instability, suggesting that while the model is performing well on the training data, it struggles to generalize to validation data. Ideally, both training and validation loss should decrease together, but in this case, the validation loss increases irregularly, confirming that the model is overfitting it memorizes the training data rather than learning general patterns. The right graph further supports this conclusion by displaying the training and validation accuracy over time. The training accuracy, represented by the blue line, shows a smooth and continuous increase, reaching nearly 100%, which suggests that the model is learning the training data perfectly. However, the validation accuracy, represented by the orange line, remains low and erratic throughout training. Instead of following the upward trend of the training accuracy, it fluctuates significantly, failing to improve consistently. This indicates that while the model is highly accurate on the training set, it does not perform well on unseen data, highlighting a lack of generalization. The sharp fluctuations in validation accuracy suggest that the model is capturing noise rather than meaningful patterns in the data.

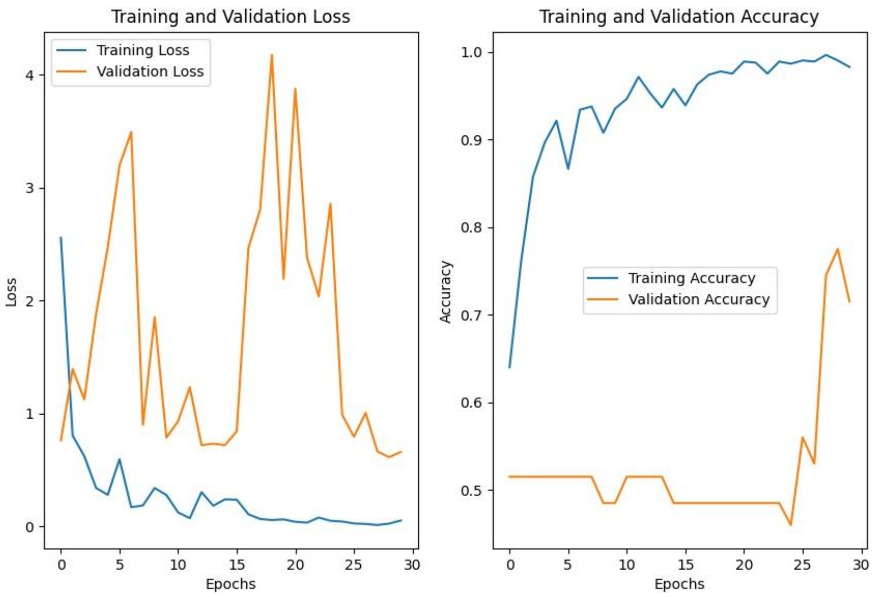

Figure 4: Overfitting Pattern

This pattern of low validation accuracy, high training accuracy, and fluctuating validation loss is a classic sign of overfitting. Overfitting occurs when a model learns not only the important relationships in the data but also memorizes minor details and noise that do not generalize to new data. To improve the model's performance and reduce overfitting, several techniques can be applied. Regularization methods, such as L1/L2 regularization or dropout, can help prevent the model from learning unnecessary patterns. Increasing the dataset size or applying data augmentation techniques can introduce more variability, making the model more robust. Additionally, early stopping can be implemented to halt training when validation loss starts increasing, preventing excessive learning from training data. Simplifying the model architecture by reducing the number of layers or neurons can also help improve generalization.

V. CONCLUSION

Advancements in CNN architectures, such as DropPath and Squeeze-and-Excitation blocks, have significantly improved plant disease detection by enhancing generalization and feature extraction. Combined with compound scaling and hybrid models, these innovations make CNNs more efficient, scalable, and accurate for real-world agricultural applications. By enabling timely disease detection, these technologies help to reduce the effect of disease on crop and support sustainable farming practices.

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