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Transforming Agriculture with AI, collaborative solutions and Image based diagnosis

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Abstract: Our project endeavors to create an all-encompassing platform that not only diagnoses plant diseases but also provides solutions for limited market access and social problems faced by farmers. By integrating advanced algorithms and leveraging data analytics, we seek to offer personalized recommendations and tailored support to farmers, thereby enhancing their productivity and profitability. Additionally, our platform promotes knowledge exchange and collaboration among stakeholders, fostering a culture of innovation and continuous improvement in agricultural practices. Through strategic partnerships and community-driven initiatives, we aim to address systemic inequalities, promote sustainable agricultural development, and create a more equitable and resilient farming ecosystem.

Keywords: ResNet, Image classification, Convolutional neural network (CNN), Data augmentation, One Cycle learning rate scheduling, Cross-entropy loss, Batch normalization, Maxpooling.

I. INTRODUCTION

Our project endeavors to revolutionize the agricultural landscape by pioneering an all-encompassing platform designed to address critical challenges faced by farmers worldwide. Agriculture, being the backbone of our society, is confronted with a myriad of obstacles ranging from plant diseases to market access issues, significantly impacting crop yield, farmer livelihoods, and global food security. Recognizing these challenges, our initiative seeks to harness the power of technology, community collaboration, and data-driven solutions to empower farmers, foster unity among farming communities, and drive sustainable agricultural practices.

At its core, our project is a testament to the transformative potential of digital innovation in agriculture. By leveraging advanced technologies such as artificial intelligence, machine learning, and data analytics, we aim to develop sophisticated diagnostic tools for plant diseases, enabling farmers to detect and mitigate crop ailments with precision and efficiency. Moreover, our platform serves as a conduit for direct engagement between farmers and consumers, bridging the gap between supply and demand and ensuring sustainable market access for agricultural produce.

Operated on public funding and driven by a commitment to collective problem-solving, our initiative is a collaborative endeavor that brings together stakeholders from across the agricultural ecosystem. Through community-driven solutions and knowledge sharing, we aspire to redefine farming practices, promote agricultural sustainability, and build resilience in the face of evolving challenges.

In Figure 1, we present an overview of the classes of plant diseases contained within our dataset, along with the corresponding number of images available for each class. This comprehensive dataset serves as the cornerstone of our endeavor, providing the foundation upon which our platform is built. With a deep understanding of the challenges faced by farmers and a data-driven approach to problem-solving, we aim to lay the groundwork for a more sustainable and interconnected agricultural landscape, where innovation thrives, communities flourish, and food security is safeguarded for generations to come.

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Plant Diseases	No.of images
Tomato___Late_blight	1851
Tomato___healthy	1926
Grape___healthy	1692
Orange___Haunglongbing_(Citrus_greening)	2010
Soybean___healthy	2022
Squash___Powdery_mildew	1736
Potato___healthy	1824
Corn_(maize)___Northern_Leaf_Blight	1908
Tomato___Early_blight	1920
Tomato___Septoria_leaf_spot	1745
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	1642
Strawberry___Leaf_scorch	1774
Peach___healthy	1728
Apple___Apple_scab	2016
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1961
Tomato___Bacterial_spot	1702
Apple___Black_rot	1987
Blueberry___healthy	1816
Cherry_(including_sour)___Powdery_mildew	1683
Peach___Bacterial_spot	1838
Apple___Cedar_apple_rust	1760
Tomato___Target_Spot	1827
Pepper,_bell___healthy	1988
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1722
Potato___Late_blight	1939
Tomato___Tomato_mosaic_virus	1790
Strawberry___healthy	1824
Apple___healthy	2008
Grape___Black_rot	1888
Potato___Early_blight	1939
Cherry_(including_sour)___healthy	1826
Corn_(maize)___Common_rust_	1907
Grape___Esca_(Black_Measles)	1920
Raspberry___healthy	1781
Tomato___Leaf_Mold	1882
Tomato___Spider_mites Two-spotted_spider_mite	1741
Pepper,_bell___Bacterial_spot	1913
Corn_(maize)___healthy	1859

There are 70295 images for training

Figure 1: Distribution of Plant Diseases in the Dataset

Additionally, in Figure 2, we showcase a selection of images depicting various plant diseases, providing a visual representation of the challenges our platform seeks to address. These images underscore the importance of accurate and efficient diagnostic tools in mitigating the impact of plant diseases on crop yield and agricultural productivity.

Figure 2: Visual Representation of Plant Diseases

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1.1 PROBLEM STATEMENT

PROBLEM:
The agricultural sector faces challenges like plant diseases, and limited market access for farmers. Lack of a centralized platform hinders problem-sharing and solving.

SOLUTION:
This project deals with plant disease diagnosis and direct farmer-consumer links. Volunteers offer verified solutions within a 3-week window, fostering community-driven problem-solving and innovative farming approaches, fue led by public funding.

1.1 OBJECTIVES
The objective of this project is:

• Algorithm Development: Develop advanced algorithms for accurate and efficient plant disease diagnosis based on uploaded images. This objective forms the core of the project's technical foundation, ensuring the platform's ability to effectively identify and classify plant diseases.

• Image Recognition Integration: Integrate cutting-edge image recognition technology to enhance the platform's diagnostic capabilities. By leveraging state-of-the-art image recognition techniques, the platform can accurately analyze and interpret images, enabling prompt and reliable diagnosis.

II. Efficient Image Processing: Implement efficient image processing techniques to handle large volumes of image data uploaded by farmers. This objective ensures the platform's scalability and responsiveness, enabling it to effectively manage and process a diverse range of agricultural images in a timely manner.

III. LITERATURE SURVEY

[1] Vinod Kumar, Hrithik Arora, and Jatin Sisodia et al introduced a ResNet-based approach for Detection and Classification of Plant Leaf Diseases, published in the proceedings of the International Conference on Computing Communication Control and Automation. Their study demonstrated that by fine-tuning parameters and employing techniques like learning rate scheduling, gradient clipping, and weight decay, ResNet achieved remarkable accuracy of 99% in image classification tasks, surpassing other models. This research underscores the effectiveness of ResNet architectures in accurately identifying and classifying plant diseases, showcasing their superiority over traditional methods.

[2] G.P. Saradhi Varma, Satti R.G. Davuluri et al introduced a novel approach titled "ResNet-based modified Red Deer Optimization with DLCNN classifier for plant disease identification and classification" at the International Conference on Computing Communication Control and Automation in 2023. Their study, utilizing ResNet and DLCNN classifier, focused on plant disease identification and classification using datasets from Plant Village and Rice Plant Disease. Implemented through Anaconda Distribution software in Python, their system incorporated training and testing processes to evaluate performance metrics, achieving a notable 93% accuracy in disease detection and classification. The research underscores the importance of automated methods in addressing challenges associated with manual crop disease inspection, emphasizing the critical role of early disease detection in global food production and quality maintenance.

[3] Smitha Pad Shetty and Ambika et al introduced a novel approach for plant leaf disease detection utilizing the Leaky Rectilinear Residual Network (LRRN) model, evaluated against existing methodologies such as HRF-MCSVM, MF3 R-CNN, OMN-CNN, and CNN-VGG19. Their proposed model achieved remarkable performance metrics, including an accuracy of 94.56%, precision of 93.48%, recall of 93.12%, F1-score of 93.82%, and specificity of 92.58%. The study underscores the significance of leveraging advanced deep learning techniques to enhance disease detection in plants. By surpassing previous methods, the LRRN model demonstrates superior effectiveness in identifying and classifying plant leaf diseases, thereby advocating for its adoption in precision agriculture practices.

[4] Muhammad Shoaib, Bilal Shah, Syed Ehsan-ul-Haque et al conducted a thorough investigation on plant disease detection using advanced deep learning techniques, specifically focusing on ResNet technology. Their research aimed at improving the accuracy and efficiency of disease detection compared to conventional manual methods. They emphasized the importance of

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developing generalizable models capable of detecting diseases across various plant species and highlighted the necessity of accessible datasets for training and evaluating machine learning and deep learning models in this field.

[5] Kalpana Chowdary and Jude Hemanth et al explored the effectiveness of DenseNet-121, ResNet-50, and VGG-16 in the early diagnosis and classification of plant diseases in crops. Their study revealed that DenseNet-121 outperformed ResNet-50 and VGG-16, as well as Inception V4, in terms of classification accuracy, sensitivity, specificity, and F1 score. DenseNet-121 demonstrated reduced training complexity and achieved remarkable results, with a classification accuracy of 99.81% and an F1 score of 99.8%. The validation accuracy for DenseNet-121 was exceptionally high, approaching an F1 score of 1, indicating outstanding performance. This research underscores the significance of implementing advanced deep learning technologies, such as DenseNet-121, for accurate and efficient plant disease identification in agriculture.

[6] Nindra Chandu and N. Bharatha Devi conducted a comparative study published in Eur. Chem. Bull. 2023, examining ResNet and Support Vector Machine (SVM) for plant disease detection. Their research revealed ResNet's superior accuracy over SVM, employing statistical analysis tools like SPSS and a sample size of 20. The study detailed ResNet's algorithm steps, highlighting the importance of data normalization and feature selection. Furthermore, it emphasized the critical role of timely disease detection in preventing plant bacteria harm and enhancing economic outcomes.

[7] The document, authored by Dr. T. Praveen Blessington, Bhargav Krishnan, Yash Bharne, Kartiki Khoje, and Prathamesh Padwal from Zeal College of Engineering and Research, discusses leaf disease detection using deep learning techniques, published in the International Journal of Creative Research Thoughts (IJCRT). Their research aims to enhance agricultural productivity by automating plant disease recognition. The proposed method involves employing a ResNet model, which exhibits superior performance compared to other deep learning models. Through the utilization of image processing and Convolutional Neural Networks (CNN), early detection and identification of leaf diseases can significantly reduce crop losses and improve yield. The study underscores the importance of technology integration in agriculture for early disease detection and mitigation. The application of deep learning in plant disease recognition shows promising results in minimizing drawbacks associated with traditional methods. The authors provide insights into the system architecture, key libraries like Keras and TensorFlow, and project design to facilitate effective leaf disease detection.

IV. PROPOSED DESIGN & METHODOLOGY

The following design shows the procedure that will be followed in our project:

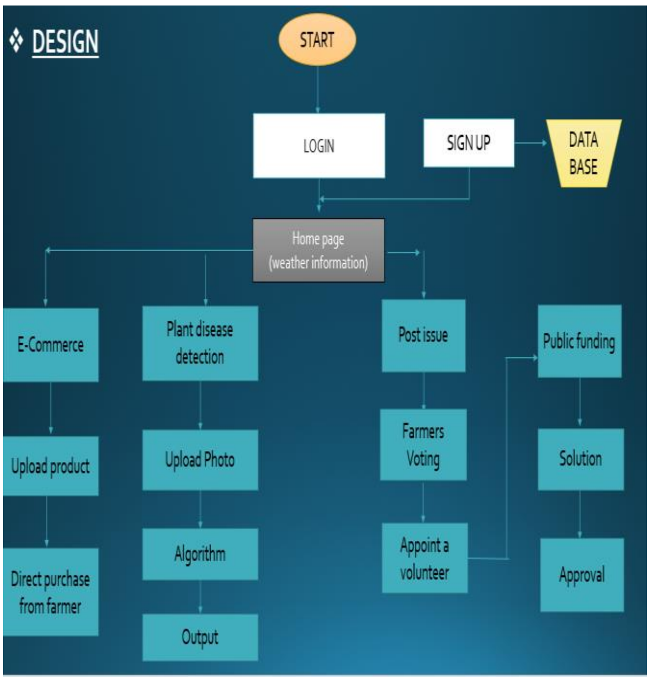

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Figure 3: Flow Diagram of proposed model

The flowchart elegantly illustrates the seamless traversal across three pivotal features: E-commerce, Plant Disease Detection, and Post-Issue Resolution. Each segment operates autonomously yet harmoniously, orchestrating a symphony of functionalities aimed at enhancing agricultural resilience and productivity.

At the heart of this design lies a commitment to empower farmers beyond the realms of traditional e-commerce. The platform emerges as a dynamic nexus, fostering a vibrant ecosystem of knowledge exchange, collaborative problem-solving, and economic empowerment within the agricultural domain.

With intuitive navigation pathways and interconnected functionalities, the flowchart embodies our vision of a digitally-enabled agricultural community, where innovation thrives, challenges are met head-on, and prosperity flourishes.

We propose a novel approach inspired by the principles of ResNet-50 a convolutional neural network renowned for its effectiveness in computer vision tasks. Our methodology builds upon the core idea of utilizing residual connections to mitigate the vanishing gradient issue and facilitate the training of deeper models.

Our model architecture consists of multiple stages, each comprising convolutional and identity blocks. These blocks are designed to extract and refine features from input images through successive layers of convolution and non-linear transformations. Crucially, our model incorporates skip connections that enable the direct propagation of information from earlier layers to subsequent layers, thereby facilitating gradient flow and preventing the degradation of performance with increasing depth.

In our methodology, we define the residual mapping function, denoted as $H(x)$, which represents the difference between the output of the non-linear layers ($F(x)$) and the input image (x). Mathematically, this can be expressed as $H(x) = F(x) + x$, where x is the input image.

Furthermore, our methodology emphasizes the importance of training data augmentation, regularization techniques, and optimization strategies to enhance model generalization and robustness. We employ techniques such as data augmentation, dropout regularization, and adaptive learning rate scheduling to prevent overfitting and improve convergence during training.

In addition to the core principles of ResNet-50, our approach integrates a novel ensemble learning technique that leverages the collective intelligence of multiple models to enhance prediction accuracy and robustness. By combining the predictions of diverse models trained on different subsets of data or using distinct architectures, we aim to mitigate the risk of individual model biases and errors, resulting in more reliable and trustworthy outcomes. This ensemble strategy not only enriches the diversity of insights derived from the data but also fosters resilience against noise and outliers, ultimately bolstering the efficacy of our solution in real-world scenarios.

Overall, our methodology harnesses the principles of residual connections and advanced neural network architecture to develop a powerful and efficient model for addressing complex computer vision tasks. Through rigorous experimentation and evaluation, we validate the effectiveness and performance of our proposed approach across various benchmark datasets and real-world applications.

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```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1        [-1, 64, 256, 256]           1,792
       BatchNorm2d-2        [-1, 64, 256, 256]             128
              ReLU-3        [-1, 64, 256, 256]               0
            Conv2d-4       [-1, 128, 256, 256]          73,856
       BatchNorm2d-5       [-1, 128, 256, 256]             256
              ReLU-6       [-1, 128, 256, 256]               0
         MaxPool2d-7         [-1, 128, 64, 64]               0
            Conv2d-8         [-1, 128, 64, 64]         147,584
       BatchNorm2d-9         [-1, 128, 64, 64]             256
             ReLU-10         [-1, 128, 64, 64]               0
           Conv2d-11         [-1, 128, 64, 64]         147,584
      BatchNorm2d-12         [-1, 128, 64, 64]             256
             ReLU-13         [-1, 128, 64, 64]               0
           Conv2d-14         [-1, 256, 64, 64]         295,168
      BatchNorm2d-15         [-1, 256, 64, 64]             512
             ReLU-16         [-1, 256, 64, 64]               0
        MaxPool2d-17         [-1, 256, 16, 16]               0
           Conv2d-18         [-1, 512, 16, 16]       1,180,160
      BatchNorm2d-19         [-1, 512, 16, 16]           1,024
             ReLU-20         [-1, 512, 16, 16]               0
        MaxPool2d-21           [-1, 512, 4, 4]               0
           Conv2d-22           [-1, 512, 4, 4]       2,359,808
      BatchNorm2d-23           [-1, 512, 4, 4]           1,024
             ReLU-24           [-1, 512, 4, 4]               0
           Conv2d-25           [-1, 512, 4, 4]       2,359,808
      BatchNorm2d-26           [-1, 512, 4, 4]           1,024
             ReLU-27           [-1, 512, 4, 4]               0
AdaptiveAvgPool2d-28           [-1, 512, 1, 1]               0
          Flatten-29                  [-1, 512]               0
           Linear-30                   [-1, 38]          19,494
================================================================
Total params: 6,589,734
Trainable params: 6,589,734
Non-trainable params: 0
----------------------------------------------------------------
```

Figure 4: Overview of ResNet-50 Architecture

In Figure 4, we present a detailed breakdown of the architectural components and parameters of our proposed methodology. The figure provides insights into the layers, output shapes, and parameter counts of each component within the model.

Starting with the convolutional layers, the figure outlines the input shape and output shape of each layer, along with the corresponding number of parameters. Batch normalization and rectified linear unit (ReLU) activation functions are applied after each convolutional operation to enhance the stability and non-linearity of the network.

The convolutional layers are followed by max-pooling operations, which down sample the feature maps to capture the most salient information while reducing computational complexity. Subsequently, identity blocks are employed to refine the features extracted by the convolutional layers.

The adaptive average pooling layer aggregates spatial information from the feature maps and produces a compact representation suitable for classification tasks. Finally, a fully connected linear layer maps the extracted features to the output classes, with a total of 38 classes in this instance.

In addition to the architectural breakdown, Figure 4 also highlights the flow of information within the network, illustrating how data propagates through different layers and transformations to ultimately produce the final output. This visualization aids in comprehending the hierarchical nature of the model, where low-level features are progressively refined into higher-level abstractions through successive layers of computation. By depicting the sequence of operations performed at each stage of the network, Figure 4 elucidates the inner workings of our methodology, shedding light on the intricate processes involved in feature extraction and classification.

Furthermore, the detailed analysis provided in Figure 4 offers valuable insights into the computational efficiency and resource utilization of our proposed methodology. By quantifying the number of parameters associated with each component and layer, the figure enables an assessment of the model's complexity and scalability. This information is instrumental in optimizing the model for deployment on resource-constrained platforms or in scenarios where computational efficiency is paramount. Moreover, the breakdown of output shapes and dimensions facilitates a deeper

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understanding of the spatial transformations occurring within the network, elucidating how the model processes and transforms input data to make accurate predictions

Overall, Figure 4 serves as a comprehensive reference for understanding the architecture and computational characteristics of our proposed methodology, facilitating deeper insights into its design and implementation.

V. EXPERIMENTATION

Data Preparation and Preprocessing

The experimental pipeline commences with the importation of essential libraries, including PyTorch for deep learning functionalities and torch vision for image processing tasks. We meticulously set up the data directories, adhering to the structure of the New Plant Diseases Dataset. Leveraging the ImageFolder class from torch vision. datasets, we meticulously organize the dataset into training and validation sets, each containing images of diverse plant diseases and healthy specimens. To augment the training data and enhance the model's robustness, we employ a series of data augmentation techniques such as random rotation. This preprocessing step is pivotal in ensuring that the model generalizes well to unseen data and exhibits resilience to various environmental conditions.

Model Architecture and Training Strategies

The cornerstone of our experimentation lies in the utilization of the ResNet-9 architecture, renowned for its efficacy in image classification tasks. Comprising a series of convolutional layers, residual blocks, and a classifier, ResNet-9 serves as the backbone of our deep learning model. We initialize the model with random weights and seamlessly transfer it to the GPU for accelerated training using CUDA, thus capitalizing on the computational prowess of modern graphics processing units. To optimize the model's performance and foster efficient convergence, we employ the Adam optimizer with a One Cycle learning rate scheduler. Throughout the training process, we meticulously monitor both training and validation losses, alongside accuracy metrics, to gauge the model's efficacy and identify potential areas for improvement.

Hyperparameter Tuning and Optimization

Hyperparameter tuning plays a pivotal role in fine-tuning the model's parameters to achieve optimal performance. We embark on a systematic exploration of hyperparameter space, varying key parameters such as the learning rate, weight decay, and gradient clipping threshold across multiple experiments. Leveraging techniques such as grid search or random search, we meticulously evaluate different combinations of hyperparameters, seeking to maximize the model's accuracy on the validation set while mitigating the risk of overfitting. This iterative process of hyperparameter optimization is crucial in refining the model's architecture and enhancing its predictive capabilities.

Model Evaluation and Performance Metrics

Following the training phase, we rigorously evaluate the model's performance on the validation set, employing a suite of performance metrics to assess its efficacy. In addition to accuracy, we compute metrics such as precision, recall, and F1-score to provide a comprehensive understanding of the model's strengths and weaknesses. By analysing these metrics, we gain valuable insights into the model's ability to correctly classify plant diseases and healthy specimens, thereby facilitating informed decision-making in agricultural management practices.

Prediction Procedures and Inference Mechanisms

To demonstrate the practical utility of the trained model, we showcase the prediction procedures for identifying plant diseases in new images. Given the path to a new image, the model performs inference using forward propagation, yielding probabilistic predictions for each class. By selecting the class with the highest probability, the model assigns a corresponding label to the input image, enabling rapid and accurate diagnosis of plant diseases. This inference mechanism serves as a valuable tool for farmers and agricultural experts, empowering them to swiftly identify and mitigate crop health issues.

VI. TESTING AND RESULTS

Figure 5 illustrates the training progress of the model over successive epochs, demonstrating the improvement in accuracy as the training proceeds. At the outset, the model starts with an initial accuracy of 0, reflecting its random initialization. As training progresses, the accuracy steadily increases, reaching 80% at epoch 1 and further surging to an impressive 98% at epoch 2. The plot serves as a visual representation of the model's learning process, highlighting its ability to iteratively refine its predictions and achieve higher accuracy with each epoch.

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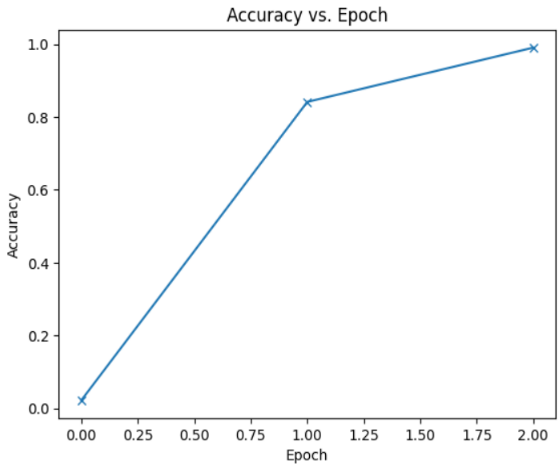

Figure 5: Training Progress: Accuracy vs. Epoch

The training progress and performance metrics for each epoch are summarized below:

Epoch 0:
Training Loss: 0.2690
Validation Loss: 0.3411
Validation Accuracy: 88.99%

Epoch 1:
Training Loss: 0.2433
Validation Loss: 0.0720
Validation Accuracy: 97.68%

Epoch 2:
Training Loss: 0.1158
Validation Loss: 0.0297
Validation Accuracy: 99.08%

These metrics provide insights into the model's training dynamics and its performance on the validation dataset across different epochs. The decreasing trend in both training and validation losses, coupled with the increasing validation accuracy, reflects the model's ability to learn and generalize effectively over successive epochs. Furthermore, the diminishing learning rate indicates that the model approaches convergence, achieving remarkable accuracy while minimizing loss.

```
Epoch [0], last_lr: 0.00099, train_loss: 0.2690, val_loss: 0.3411, val_acc: 0.8899
Epoch [1], last_lr: 0.00046, train_loss: 0.2433, val_loss: 0.0720, val_acc: 0.9768
Epoch [2], last_lr: 0.00000, train_loss: 0.1158, val_loss: 0.0297, val_acc: 0.9908
```

Figure 6: Training Progress and Performance Metrics

Figure 7 depicts the initial stage of image processing and prediction within our system. Upon user input of an image file, the system preprocesses the image through various transformations, including resizing and normalization, to standardize its format for analysis. Following preprocessing, the model then utilizes advanced algorithms to make accurate predictions regarding the presence or absence of plant diseases, ensuring precise and reliable outcomes for agricultural stakeholders.

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```
predicted_class = predict_single_image(image_path, model, class_names)
print(f"Predicted Class: {predicted_class}")
```

```
/kaggle/input/new-plant-diseases-dataset/New Plant Diseases Dataset(Augmented)/New Pla
sh__Powdery_mildew/00cfd4c7-4ccd-45a8-813c-f1cb01147aed___UMD_Powd.M 0108.JPG
1/1 [==============================] - 0s 30ms/step
Predicted Class: Squash__Powdery_mildew
```

Figure 7: Image Processing and Prediction

VII. CONCLUSION

In conclusion, our experimentation endeavours to advance the state-of-the-art in plant disease classification through a rigorous and systematic approach. By meticulously designing experiments, optimizing hyperparameters, and evaluating model performance, we aim to develop a robust and reliable deep learning model for agricultural applications. Looking ahead, future research directions may involve exploring novel architectures, integrating multi-model data sources, and deploying the model in real-world agricultural settings to assess its scalability and practical utility. Through continuous innovation and collaboration, we strive to revolutionize crop health management practices and contribute to the global sustainability of agricultural systems.

VIII. FUTURE WORK

Future research in plant disease detection and classification could concentrate on several crucial aspects to propel the field forward. Integrating multi-modal data sources like hyperspectral and thermal imaging could offer complementary insights for more comprehensive diagnosis. Tailoring transfer learning techniques could boost model performance on domain-specific datasets. Enhancing model interpretability through explainable AI methods could provide actionable insights for disease management. Designing real-time detection systems for field deployment using portable devices would enable timely interventions. Expanding research to cover a broader spectrum of plant species and diseases would enhance the applicability of detection models. Investigating automated monitoring systems and their integration with precision agriculture practices could optimize resource allocation and minimize environmental impact. Ensuring model robustness and generalization across varied conditions is crucial for real-world efficacy. Collaboration among computer scientists, agronomists, and plant pathologists could leverage domain expertise for more relevant solutions. These endeavors aim to bolster agricultural productivity, food security, and sustainability through advanced plant disease detection technologies.

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