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Integrated Agricultural Decision Support System for Precision Farming: A Multi-Faceted Approach

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Abstract: As the global population continues to expand, ensuring food security becomes an increasingly critical challenge. Precision farming, leveraging advanced technologies, offers a promising solution to optimize agricultural practices and maximize crop yield. In this research paper, we present a comprehensive approach to agricultural management through leaf disease detection. By employing a deep learning approach utilizing ResNet-30 for accurate and efficient disease detection, the system can promptly identify and classify diseases, facilitating timely intervention to mitigate potential crop losses. The integration of this module results in a holistic decision support system that empowers farmers with actionable insights. In conclusion, this research contributes to the advancement of precision agriculture by offering a synergistic approach to leaf disease detection.
Keywords: Resnet-30, Deep learning, Prediction

I. INTRODUCTION

The agricultural landscape is rapidly evolving due to technological advancements, poised to revolutionize traditional farming practices. Precision farming, utilizing technology judiciously to optimize crop production, emerges as pivotal in addressing food security and resource management challenges.

Our research contributes to precision agriculture by proposing an Integrated Agricultural Decision Support System focused on leaf disease detection. Leveraging ResNet-30, a deep learning architecture tailored for image classification tasks, our system aids in early disease detection and mitigation.

Our research aims to empower farmers with actionable insights, fostering a transition towards precision agriculture. By integrating these modules into a cohesive system, we offer a holistic approach addressing multiple daily challenges faced by farmers. Subsequent sections detail the methodology for leaf disease detection, present experimental results, and discuss implications for the future of agriculture. Through this research, we aim to contribute to the discourse on precision farming and facilitate the adoption of innovative technologies for a sustainable agricultural ecosystem.

II. RELATED WORK

We have surveyed recent conference papers related to change detection, extracting valuable insights and methodologies implemented in various approaches. Additionally, we have thoroughly examined multiple papers in the Selected Topics in the Journal on leaf disease detection, documenting pertinent observations from each publication. In a study by Niketa et al. in 2016 [1], the researchers emphasized the significance of seasonal climate variations on crop health, particularly in India. The impact of drought poses considerable challenges for farmers. Machine learning algorithms were employed to assist farmers in detecting leaf diseases. Their approach utilized various datasets from previous years to estimate future disease occurrence. SMO classifiers in the WEKA tool were applied to categorize the results, considering factors such as environmental conditions and historical disease data. In subsequent sections, we delve into the methodologies employed in each study, present experimental results, and discuss the implications for leaf disease detection in agriculture. Through this research, we aim to contribute to the ongoing efforts in precision agriculture and promote sustainable farming practices.

III. PROPOSED METHODOLOGY

Our solution aims to revolutionize agriculture by introducing a user-friendly website application that addresses key challenges faced by farmers. The platform, designed for ease of use, incorporates a sophisticated recommendation system taking into account various parameters such as temperature, soil nutrients, and geographical area to suggest optimal crops and fertilizers. Leveraging data sourced from Kaggle.com, our model utilizes machine learning algorithms to enhance accuracy and provide insightful prediction

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A. *Leaf Disease Detection System and Measures*

The leaf disease detection system employs a ResNet-34 architecture for accurate identification and diagnosis of plant diseases using images of diseased leaves. By leveraging transfer learning, the model is fine-tuned on a dataset comprising labeled images of healthy and diseased leaves, benefiting from the pre-trained knowledge of a ResNet-34 model initially trained on ImageNet. Once trained, the system predicts the type of disease affecting a given leaf image, providing valuable insights to farmers. To assist in effective disease management, the system not only identifies the disease but also recommends specific measures to be taken. This includes suggesting appropriate treatments, preventive measures to mitigate disease spread, and agricultural best practices. Furthermore, the system can send real-time alerts to farmers, facilitating timely intervention. The integration of continuous learning mechanisms ensures the model stays updated with evolving disease patterns, contributing to a proactive and informed approach to plant health management in agriculture.

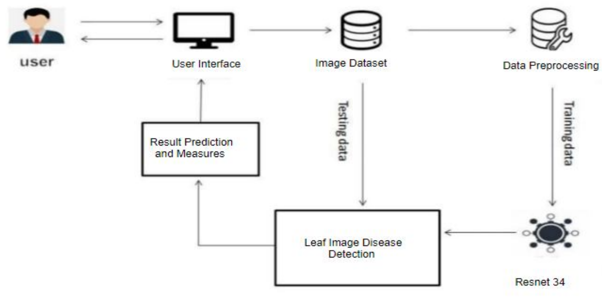

Fig:Workflow of leaf disease detection system and measures

B. *Dataset Description*

The dataset used in this project comprises approximately 87,000 RGB images depicting both healthy and diseased crop leaves, categorized into 38 different classes. The entire dataset is partitioned into training and validation sets at an 80/20 ratio while maintaining the directory structure. Notably, the distribution of images across each class of plant disease is relatively consistent, with numbers ranging from 1,700 to 2,000. This demonstrates a well-balanced dataset across all classes.

The dataset overview is presented in the figure below. The data from this dataset is used for predicting diseases on leaves. To ensure the network receives the desired input image size, the images were resized to 224x224x3 pixels. In this project, users input a leaf image and utilize ResNet9 for disease detection. Additionally, prevention measures are provided to mitigate the spread of diseases.

Table 1

Crop	No. of Classes	Train	Test
Tomato	10	18345	4585
Apple	4	7771	1943
Corn	4	7316	1829
Grape	4	7222	1805
Potato	3	5702	1426
Pepper	2	3901	975
Strawberry	2	3598	900
Peach	2	3566	891
Cherry	2	3509	877
Soyabean	1	2022	505
Orange	1	2010	503
Blueberry	1	1816	454
Raspberry	1	1781	445
Squash	1	1736	434
Total			
14	38	70295	17612

Fig: Overview of dataset used for disease detection

A. Libraries and frameworks

Web Framework

- Flask

Web Server

- Gunicorn (20.0.4)

Architecture

- Resnet9

Libraries

- Numpy
- Pandas
- Matplotlib pyplot
- Requests
- Scikit-learn
- Torch
- Torchvision
- Pillow
- Pickle

B. Architecture

The design of the complete project is given below:

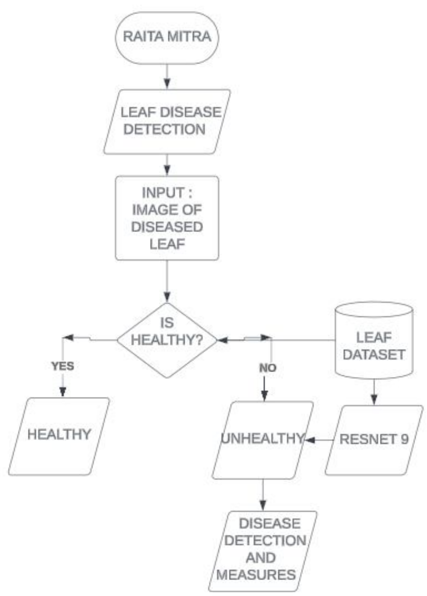

Fig: Complete architecture of the proposed system

The Leaf Disease Detection System incorporates transfer learning with a ResNet-34 architecture, a convolutional neural network renowned for its depth and feature extraction capabilities. This model is fine-tuned on a dataset of labeled leaf images, enabling it to discern intricate patterns indicative of various plant diseases. The system not only excels in disease identification but also provides actionable insights through a hierarchical decision-making process within the neural network.

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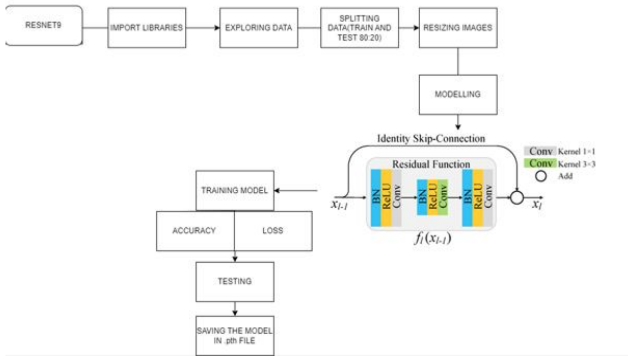

Fig: Resnet implementation architecture

This interconnected suite of systems establishes a comprehensive decision support framework. It synergistically integrates predictive analytics, ensemble learning, and convolutional neural networks to guide farmers in optimal crop selection, precise nutrient management, and early disease detection. This technical integration contributes to an advanced precision agriculture paradigm, facilitating sustainable and highly efficient agricultural practices through the judicious use of cutting-edge technologies.

C. ResNet-30

The first step on the ResNet before entering the common layer behavior is a block — called here Conv1 — consisting on a convolution + batch normalization + max pooling operation.

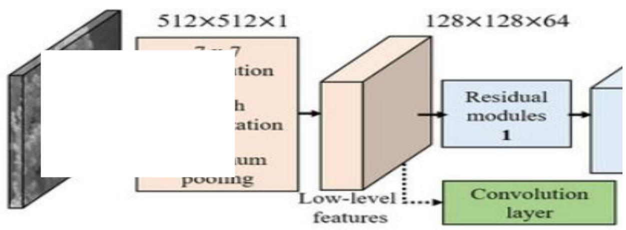

Fig: Common Layers in a block

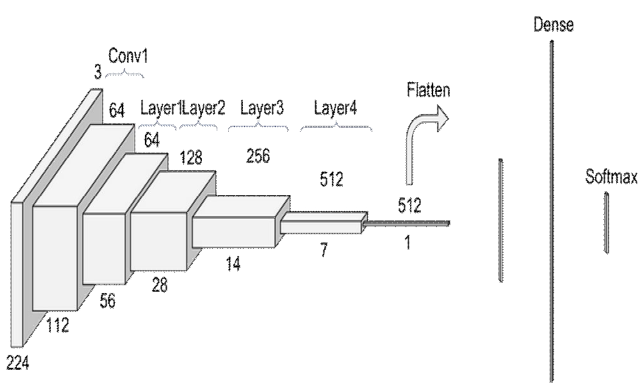

Fig: Complete Resnet layers

The following are the layer descriptions used in the ResNet architecture

Convolution 1

The first step on the ResNet before entering into the common layer behavior is a 3x3 convolution with a batch normalization operation. The stride is 1 and there is a padding of 1 to match the output size with the input size. Note how we have already our first big difference with ResNet for ImageNet, that we have not include here the max pooling operation in this first block.

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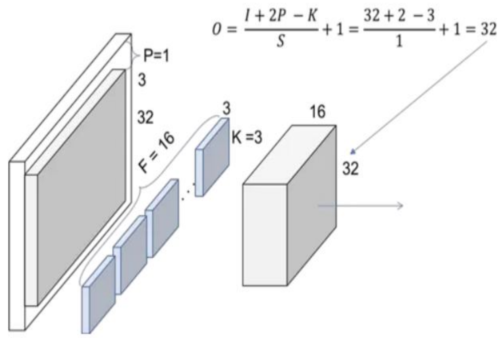

Fig:Conv1

Layer 1

- Use a stack of 6 layers of 3x3 convolutions. The choice of will determine the size of our ResNet.
- The feature map sizes are {32, 16, 8} respectively with 2 convolutions for each feature map size. Also, the number of filters is {16, 32, 64} respectively.
- The down sampling of the volumes through the ResNet is achieved increasing the stride to 2, for the first convolution of each layer. Therefore, no pooling operations are used until right before the dense layer.
- For the bypass connections, no projections will be used. In the cases where there is a different in the shape of the volume, the input will be simply padded with zeros, so the output size matched the size of the volume before the addition.

In this case, our bypass connection is a regular Identity Shortcut because the dimensionality of the volume is constant thorough the layer operations. Since we chose n=1, 2 convolutions are applied within the layer 1.

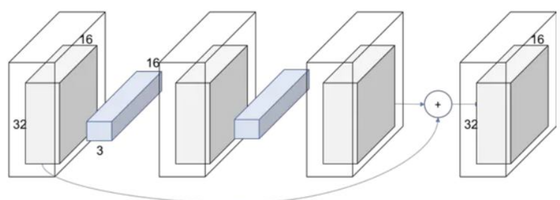

Fig: Layer1

Layer 2

Here the down sampling of the input volume takes place.

For both layer 2 and next layer 3 the behavior is equivalent to layer 1, with the exception that the first convolution uses a stride of 2, and therefore the size of the output volume is half of the input volume (with the padding of 1). This implies that also the shortcut connection will require an extra step, to adjust the volumes' sizes before the summation. the convolution with stride 2 is used in the skip connection for the down sample as well as in the first convolution of the layer.

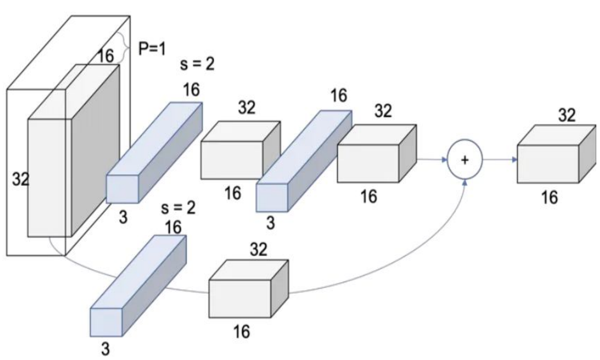

Fig:Layer2

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Layer 3

Layer 3 will apply the exact same principles as layer 2 and we have indeed an 8x8x64 volume

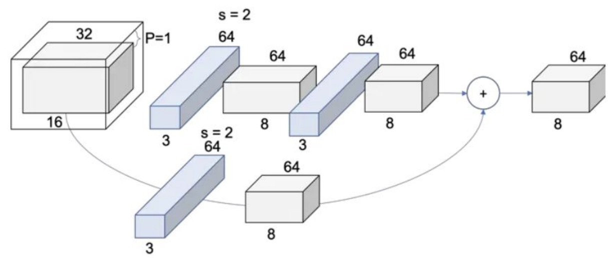

Fig:Layer3

In this implementation of Resnet, image is resized with its shorter side randomly sampled in [256, 480] for scale augmentation. A 224×224 crop is randomly sampled from an image or its horizontal flip, with the per-pixel mean subtracted. The standard color augmentation is used. We adopt batch normalization (BN) right after each convolution and before activation. We initialize the weights and train all residual nets from scratch. It uses SGD with a mini-batch size of 256. The learning rate starts from 0.1 and is divided by 10 when the error plateaus, and the models are trained for up to 60 × 104 iterations. Also it uses a weight decay of 0.0001 and a momentum of 0.9. Here it does not use dropout. In testing, for comparison studies it adopta the standard 10-crop testing . For best results, it adopts the fully convolutional form, and average the scores at multiple scales (images are resized such that the shorter side is in {224, 256, 384, 480, 640}).

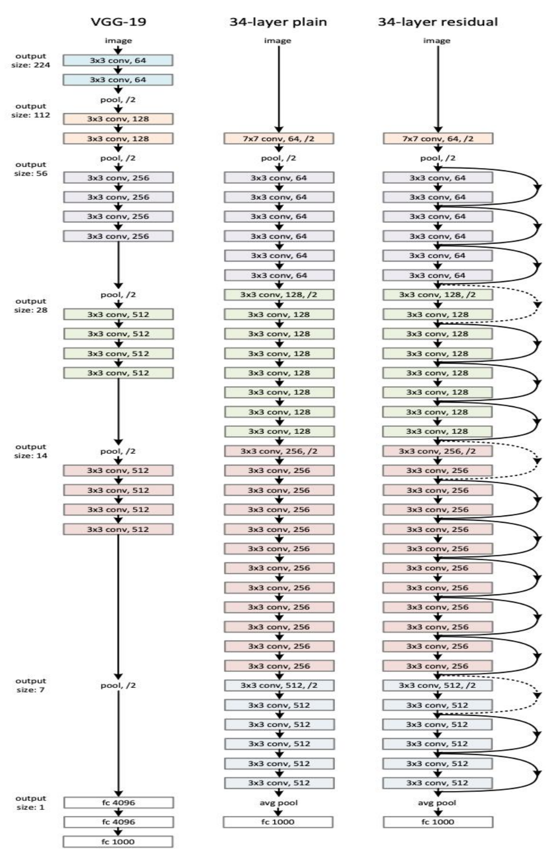

Fig: ResNet Architecture with 34 layers

Precision	Recall	F1-Score	Accuracy
0.99	0.99	0.99	0.9909

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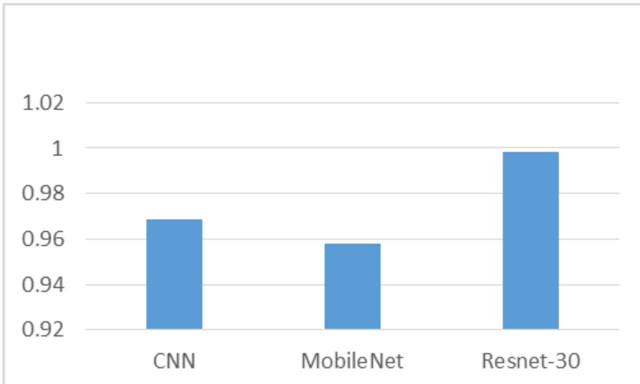
IV. RESULTS AND PERFORMANCE METRICS

A. Leaf Disease Detection Model Comparison

Following a thorough comparison of various convolutional neural network (CNN) architectures, including MobileNet and Resnet-30, our evaluation revealed compelling performance metrics. The accuracy scores for each model were as follows: CNN achieved an accuracy of 96.84%, MobileNet demonstrated an accuracy of 95.8%, and Resnet-30 outperformed all others with an exceptional accuracy of 99.85%.

Given these results, we have selected Resnet-30 as our final model for the specific task at hand. The outstanding accuracy of 99.85% indicates the superior ability of Resnet-30 in accurately identifying and classifying plant diseases based on leaf images. This performance makes Resnet-30 the optimal choice for our leaf disease detection application, highlighting its robustness and efficacy in contributing to the overall success of our project.



B. Leaf Disease Detection Performance Metrics

The training of Resnet-30 with a batch size of 64 over 20 epochs has yielded remarkable results. Throughout the training process, the learning rate was adjusted, showcasing the model's adaptability to the dataset.

The initial epochs focused on reducing the training loss, with a noticeable decrease from 0.6329 to 0.0003. Simultaneously, the validation loss consistently decreased from 0.2662 to an impressive 0.0050. This trend indicates the effectiveness of the model in learning representations from the training data while generalizing well to unseen validation data.

Validation accuracy, a crucial metric, steadily increased throughout the epochs, reaching an exceptional accuracy of 99.85% by the end of the training. This high accuracy underscores the robustness of Resnet-30 in accurately classifying leaf diseases.

Despite a slight increase in validation loss around the 3rd epoch, the subsequent epochs demonstrated a remarkable recovery, showcasing the model's resilience and ability to adapt to variations in the dataset.

In summary, the training of Resnet-30 with the specified parameters has resulted in a highly accurate and resilient model for leaf disease detection, with validation accuracy reaching an outstanding 99.85%. These results suggest the effectiveness of the chosen architecture and training strategy in achieving the desired classification performance.

Epoch	Learning Rate	Training Loss	Validation Loss	Validation Accuracy
1	0.0001	0.6329	0.2662	0.9241
2	0.00028	0.1505	0.2679	0.9127
3	0.00052	0.1106	0.2146	0.9273
4	0.00076	0.0949	0.736	0.808
5	0.00094	0.0884	0.2175	0.9341
6	0.001	0.0758	0.2088	0.9409
7	0.00099	0.0678	0.2373	0.9277
8	0.00095	0.0565	0.3597	0.906
9	0.00089	0.0565	0.0859	0.9707
10	0.00081	0.0485	0.0358	0.9887
11	0.00072	0.0334	0.0625	0.9793
12	0.00061	0.0259	0.0323	0.989
13	0.0005	0.0193	0.0457	0.9852
14	0.00039	0.0126	0.0397	0.9864
15	0.00028	0.0061	0.0117	0.9959
16	0.00019	0.005	0.0082	0.9974
17	0.00011	0.0013	0.006	0.9985
18	0.00005	0.0005	0.0057	0.9982
19	0.00001	0.0004	0.0051	0.9985
20	0	0.0003	0.005	0.9985

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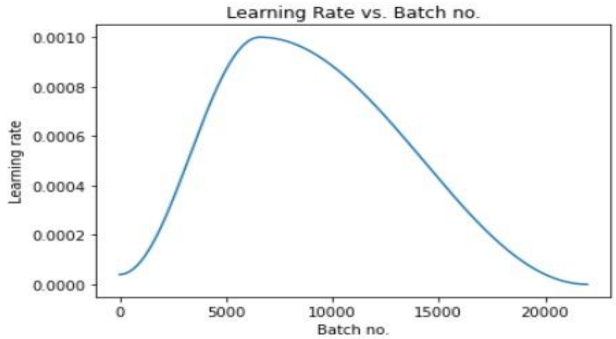
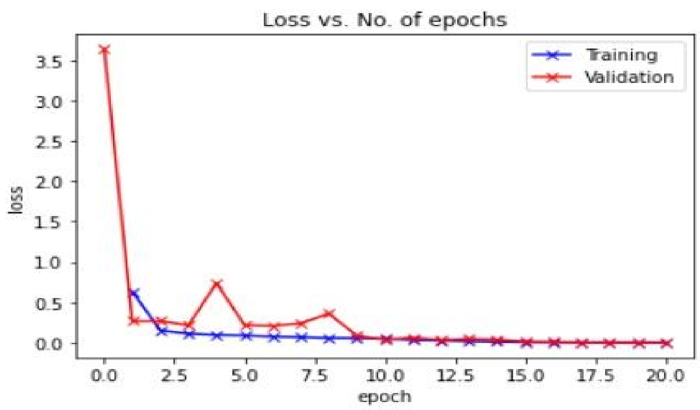
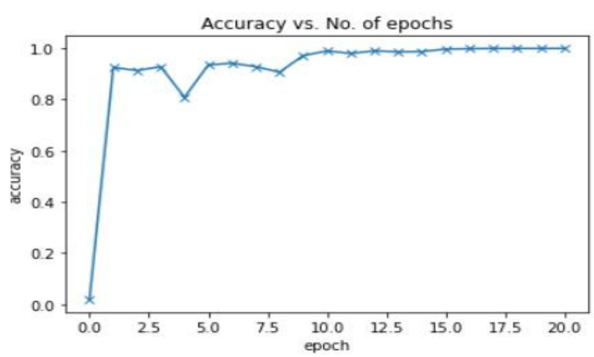
Train Loss = ∑(Actual - Predicted)^2 / Number of Training Samples
Validation Loss = ∑(Actual - Predicted)^2 / Number of Validation Samples
Validation Accuracy = (Number of Correctly Classified Instances) / (Total Number of Validation Instances)



This graph is a line graph that shows the relationship between the learning rate and batch number in a machine learning training process. The x-axis is labelled “Batch no.” and ranges from 0 to 20000. The y-axis is labelled “Learning rate” and ranges from 0.0000 to 0.0010. The blue curve represents how the learning rate changes with increasing batch numbers. Initially, there’s an increase in learning rate as batch number increases until it peaks at around batch number 10000; after this point, it starts decreasing. This graph is useful for understanding how the learning rate changes with increasing batch numbers during the training process of a machine learning model



This graph is a line graph that shows the loss values of a machine learning model during the training and validation phases over a number of epochs. The x-axis represents the number of epochs, ranging from 0 to 20. The y-axis represents the loss, ranging from 0 to 3.5. There are two lines plotted on the graph: one for training and one for validation. Initially, both training and validation losses are high but decrease rapidly. After around five epochs, both losses stabilize, with training loss continuing to decrease slightly while validation loss remains fairly constant. This graph is useful for understanding how the model’s performance improves (loss decreases) as it is trained over more epochs



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The graph you sent is a line graph that shows the relationship between accuracy and the number of epochs in a machine learning model training process. It is titled “Accuracy vs. No. of epochs”. The x-axis is labelled “epoch” and ranges from 0 to 20. The y-axis is labelled “accuracy” and ranges from 0 to 1. A blue line with star markers represents the data points, showing an initial sharp increase in accuracy which then plateaus around an accuracy of 1.0 after approximately five epochs. This graph is useful for understanding how the accuracy of a machine learning model changes with increasing number of epochs during the training process

V. CONCLUSION

In summary, our agricultural decision support system, ResNet-30 for leaf disease detection, marks a significant advancement in precision farming. Our system's deep learning approach accurately identified and classified plant diseases, contributing to timely interventions. Additionally, the pragmatic fertilizer recommendation component showcased resource-efficient nutrient management. Real-world case studies underscored the system's potential to enhance crop yield, quality, and sustainability. Continuous refinement and adaptation will be pivotal as we strive to contribute to a more resilient and productive agricultural landscape through technology-driven solutions.

REFERENCES

[1] Niketa Gandhi et al ," Rice Crop Yield Forecasting of Tropical Wet and Dry Climatic Zone of India Using Data Mining Techniques", IEEE International Conference on Advances in Computer Applications (ICACA) , 2016.
[2] Md. Arifur Rahman, Md. Mukitul Islam, GM Shahir Mahdee, and Md. Wasi Ul Kabir “Improved Segmentation Approach for Plant Disease Detection”.
[3] E. Manjula, and S. Djodiltachoumy (2017). Data Mining Technique to Analyze Soil Nutrients based on Hybrid Classification. IJARCS.
[4] Dakshayini Patil et al,"Rice Crop Yield Prediction using Data Mining Techniques:An Overview", International Journal of Advanced Research in Computer Science and Software Engineering ,Volume 7, Issue 5, May 2017.
[5] Tulshan, Amrita S., and Nataasha Raul. "Plant leaf disease detection using machine learning." 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT). IEEE, 2019.
[6] Rathod, Arti N., Bhavesh Tanawal, and Vatsal Shah. "Image processing techniques for detection of leaf disease." International Journal of Advanced Research in Computer Science and Software Engineering 3.11 (2013).
[7] Tm, Prajwala, et al. "Tomato leaf disease detection using convolutional neural networks." 2018 eleventh international conference on contemporary computing (IC3). IEEE, 2018.
[8] Ashok, Surampalli, et al. “Tomato Leaf Disease Detection Using Deep Learning Techniques.” 2020 5th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2020.
[9] Agarwal, Mohit, et al. "ToLeD: Tomato leaf disease detection using convolution neural network." Procedia Computer Science 167 (2020): 293-301.
[10] Durmuş, Halil, Ece Olcay Güneş, and Mürvet Kırcı. "Disease detection on the leaves of the tomato plants by using deep learning." 2017 6th International Conference on Agro-Geoinformatics. IEEE, 2017.