Machine Learning Techniques for Accelerated Diagnosis and Classification of Ash Gourd Leaf Diseases

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***Abstract*—The detection and classification of plant leaf afflictions is fault-finding for maintaining crop fitness and guaranteeing land productivity. Established ailment discovery procedures, whichfrequently depend manual check, are time-consumingand compulsive wrong, superior to delayed attacks and potential crop deficits. In reaction to these challenges, this project survey the use of advanced machine intelligence methods to specify an accurate and speedy resolution for detecting and classifying plant leaf ailments. By leveraging Vision Transformers (ViTs), a contemporary deep education construction, this project focuses on improving the precision and scalability of disease detection. Specifically, we apply ViTs to the Ash gourd dataset, aiming to surpass the performance of traditional Convolutional Neural Networks (CNNs) in identifying disease symptoms from leaf images. The proposed system utilizes the ViT model's self-attention mechanism to capture long-range dependencies in image data, leading to more accurate and robust classification outcomes.**

Keywords—Vision Transformers, Plant Leaf Disease, Image Classification, Ash gourd Dataset, Machine Learning, Self-attention Mechanism, Deep Learning

I. INTRODUCTION

The discovery and categorization of plant leaf diseases is essential for enduring crop fitness and guaranteeing land productivity. Established orders, that depend on manual check, are frequently slow, labor-exhaustive, and compulsive human error, conceivably beginning postponed attacks and significant crop damage. Furthermore, these manual methods struggle to equal the increasing scale of new farming, place big fields need to be listened steadily. To address these disadvantages, this project investigates the use of advanced machine intelligence systems to determine a more effective, fast, and precise resolution for ailment discovery. By mixing data improving and separation techniques, the project aims to considerably reinforce plant disease discovery in Ash gourd crops. Dossier augmentation helps increase the difference of preparation data by asking renewals such as turn, throwing, zooming, and brightness adaptations, that improve the model's skill to statement across various evident-experience conditions. Separation, in another way, isolates diseased regions on the leaves, admitting the system to devote effort to something the affected domains and humiliate noise from inappropriate parts of the representation.

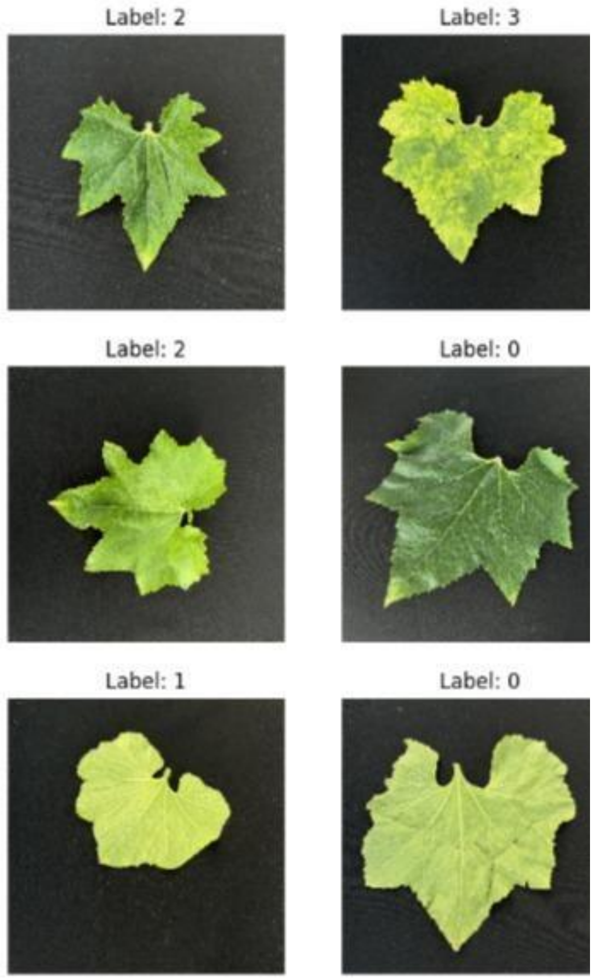


Fig.1. Sample Images

When used to the Ash gourd dataset, this approach is created to outperform established designs by improving the model's veracity, strength, and scalability. Data improving guarantees the model is less prone to overfitting, while separation admits for more exact identification of ailment manifestations, reducing two together fake positives and wrong contradiction.

In this place study, the dataset comprises concepts of athletic Ash gourd leaves alongside those affected by grainy fungus. The diseased types are further top- secret based on situations or environments labeled as KMg, K, N, and Nmg, that show different alternatives of vitamin deficiencies or situation reactions. This diverse dataset supplies the model accompanying examples of two together healthful and various unhealthy states, embellishing its skill to equate healthy leaves and distinguishing powdery fungus environments. By leveraging data improving and separation, the model can better generalize across these environments, growing the precision in recognizing quiet differences middle from two points.

II. Literature Survey

Jindal et al. [1] classified different varieties of bottle gourds, specifically from the "Pusa" group in India. They worked with a dataset of 8,200 images focused on Indian varieties for classification. Valiente et al. [2] presented an approach for detecting defects, amount, maturity, and kind in produce such as Women' Finger, Sharp Gourd, and Paper money. They secondhand MobileNetV2 along with a Boo Pi joined with area for water draining algorithms and K-way clustering for countenance convert. Data augmentation was applied, and 200 images per quality type were used for training. Hasan et al. [3] introduced the M3 model, a CNN-based approach that achieved 99.70% accuracy in detecting defects in Bitter Gourd. This model demonstrated improved performance over previous methods, showcasing the potential of CNNs in agricultural applications. Banerjee et al. [4] proposed a model that combines CNN and SVM to identify and classify five diseases affecting Ridge Gourd leaves. The model uses CNN for feature extraction and SVM for precise classification, demonstrating the influence of machine intelligence techniques in land ailment detection. Rony and others. [5] secondhand the VGG16 algorithm to recognize container gourd ailments at beginning. Their approach helped categorize differing diseases efficiently. Hasan and others. [6] bestowed the M3 model, another CNN- based approach for detecting defects in Sharp Fruit, achieving important bettering's over earlier patterns and augmenting the importance of CNNs in farming. Banerjee and others. [7] utilized CNNs and Haphazard Wood models to categorize diseases in sharp titian leaves. Their model was evaluated utilizing accuracy, recall, and F1-Score, with accuracy principles ranging from 92.85% to 95.48%, recall principles from 92.61% to 94.82%, and F1-Score varying from 93.11% to 94.67%, resulting in an overall accuracy of 98%. Jindal et al. [8] explored a Federated Learning approach combined with CNN to diagnose five common Cucurbit leaf diseases. The model was trained using data from five clients and assessed using precision, recall, and F1-score, with accuracy ranging between 96% and 99%. The Federated Learning method preserved data privacy while enabling global model building. Rani et al. [9] evaluated the performance of three pretrained CNN models (VGG16, InceptionV3, and ResNet50) to detect diseases in pepper and potato plants. ResNet50 achieved the highest accuracy at 100%, followed by VGG16 at 99%, and InceptionV3 at 96%, indicating the superiority of ResNet50 in plant disease prediction. Sharma and Brar [10] focused on classifying different varieties of bottle gourds, specifically from the "Pusa" group in India. Their study used 8,200 images for classification, with an emphasis on Indian varieties. Dube et al. [11] presented a CNN-based system for detecting tomato leaf diseases through netting-located platform place peasants can transfer data to a server leaf image to endure palpable-occasion diagnoses. The model was trained on a Kaggle dataset and attained a veracity of a 93%, providing reliable disease predictions and treatment suggestions. Hosain et al. focused on the use of transfer learning with three pretrained CNN models—InceptionV3, DenseNet201, and EfficientNetV2S—to detect five coarse edible grain leaf afflictions, containing leaf blast, bacterial leaf blight, and dark spot. DenseNet201 achieved the highest accuracy of 92.05%, showcasing the effectiveness of CNNs in enhancing early intervention in rice farming. Sebastian et al. [13] presented an approximate study of several machine intelligence and deep knowledge models, including SVM, Chance Forest, Childlike Bayes, KNN, Conclusion Tree, Sequential, and VGG16, to detect apple leaf diseases. VGG16 outperformed other methods, achieving the highest accuracy of 97.23%, proving effective in classifying healthy and diseased apple leaves. Usman et al. [14] aimed to improve the accuracy of vegetation index computation for eggplant crops using leaf segmentation techniques. The study compared U- Net and FPN architectures with VGG16 and VGG19 encoders, with FPN-VGG16 outperforming others in terms of accuracy and latency. A new dataset, Leaves AV, for eggplant leaf segmentation was also introduced. Anwar and Lamba [15] employed a methodology that involved image pre-processing, CNN-based feature extraction, and classification into eight disease categories, including Leaf Blight, Red Scab, and Brown Blight. Their approach outperformed traditional machine learning models like SVM and KNN, with potential for improvement through parameter optimization and transfer learning

III. Proposed System

Data Collection:

The dossier collection for the Ruins Fruit dataset from Kaggle involves curating first-rate concepts of Ash Fruit (also known as fuller fruit or winter melon) leaves that exhibit miscellaneous ailment symptoms in addition to athletic leaves for comparison. This dataset usually contains branded concepts that identify various types of plant ailments such as fungal contaminations, bacterial blight, or nutrient inadequacies, in addition to healthy leaf samples. The dossier is frequently sourced from palpable-world land atmospheres, with representations captured under diverse ignition environments and at different tumor stages to ensure instability and strength in disease discovery. The dataset grant permission also contain metadata such as the point of nurture, the stage of affliction progress, and other appropriate agronomic determinants. For this project, Kaggle determines a platform to approach and share the dataset accompanying a global society of machine learning experts, advancing collaboration.

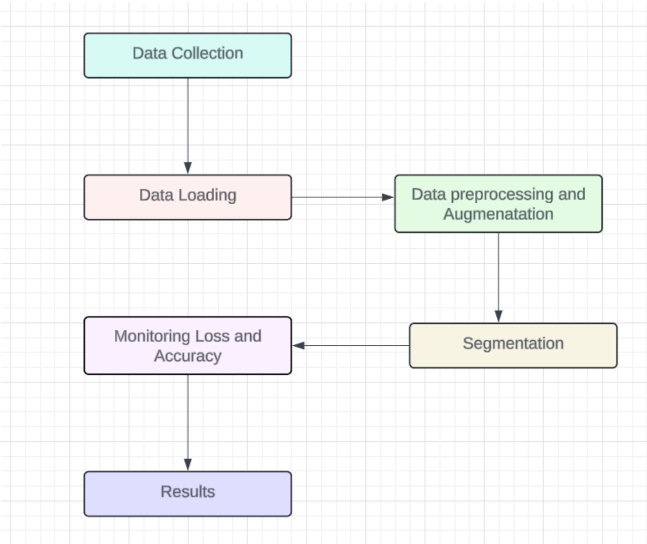


Fig.2. Process Workflow

PREPROCESSING AND AUGMENTATION:

Preprocessing and improving are essential steps in fitting the Ash Fruit dataset for preparation a machine intelligence model. Preprocessing includes cleaning and normative the countenance dossier to guarantee consistency. This involves tasks in the way that resizing countenances to a uniform breadth, converting bureaucracy to grayscale or RGB

layout, make universal pixel principles (usually middle from two points 0 and 1), and management any absent or corrupt dossier. These steps guarantee that the figures are in a suitable plan for the Fantasy Device that drives a machine (ViT) model to process efficiently.

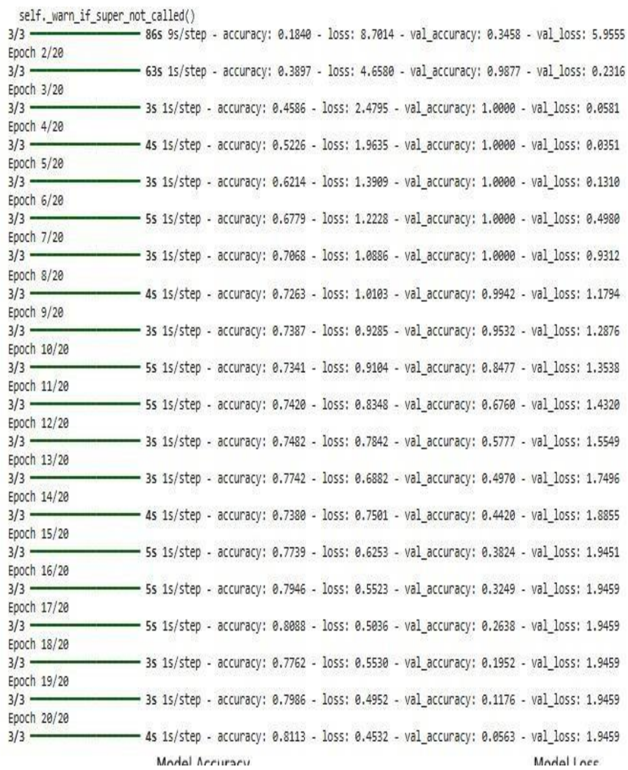
Dossier augmentation improves the dataset by artificial means increasing allure size and instability, that helps improve model inference. Methods like random rotations, level and vertical flips, zooms, shine adaptations, and shifts are applied to the figures. This process creates alternatives of the existent images, mocking honest-world sketches where illumination, angle, and adjustment may change. By incorporating these revolutions, improving reduces overfitting and enables the model to determine more robust looks, eventually improving allure accomplishment on unseen dossier.

SEGMENTATION:

Separation in the framework of the Ash Fruit dataset refers to the process of recognizing and separating particular regions of interest, in the way that unhealthy regions on the leaves, from the rest of the representation. This pixel-reasonable categorization method admits for more precise study, as it divorces the impressed parts of the leaf from the healthy one, permissive the model to devote effort to something the manifestations of disease. Separation maybe acted utilizing algorithms like U-Net , which are standard for their strength to handle complex figures and accurately describe lines. By segregating the unhealthy sections, separation upgrades the model's capability to discover subtle face guide plant ailments, chief to more accurate categorization and conceivably contribution insights into the asperity or spread of the condition. This step is specifically beneficial in big agricultural requests, place early discovery of local disease outbreaks is important for barring extensive crop damage and give the results.

IV. RESULTS AND ANALYSIS

The model manifests productive learning on the preparation dossier, as designated apiece steady decrease in preparation misfortune and the logical increase in training veracity across epochs, arriving about 80% for one 10th epoch. This progress implies that the model has a stable capacity to discover patterns inside the preparation dataset, favorably capturing appropriate features and lowering error accompanying each period. These currents focal point the robustness of the preparation process and the model's potential for correct guesses.



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 self._warn_if_super_not_called()
3/3 ━━━━━━━━━━━━━━━━━━━━ 86s 9s/step - accuracy: 0.1840 - loss: 8.7014 - val_accuracy: 0.3458 - val_loss: 5.9555
Epoch 2/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 63s 1s/step - accuracy: 0.3897 - loss: 4.6580 - val_accuracy: 0.9877 - val_loss: 0.2316
Epoch 3/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.4586 - loss: 2.4795 - val_accuracy: 1.0000 - val_loss: 0.0581
Epoch 4/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 1s/step - accuracy: 0.5226 - loss: 1.9635 - val_accuracy: 1.0000 - val_loss: 0.0351
Epoch 5/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.6214 - loss: 1.3909 - val_accuracy: 1.0000 - val_loss: 0.1310
Epoch 6/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.6779 - loss: 1.2228 - val_accuracy: 1.0000 - val_loss: 0.4980
Epoch 7/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7068 - loss: 1.0886 - val_accuracy: 1.0000 - val_loss: 0.9312
Epoch 8/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 1s/step - accuracy: 0.7263 - loss: 1.0103 - val_accuracy: 0.9942 - val_loss: 1.1794
Epoch 9/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7387 - loss: 0.9285 - val_accuracy: 0.9532 - val_loss: 1.2876
Epoch 10/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.7341 - loss: 0.9104 - val_accuracy: 0.8477 - val_loss: 1.3538
Epoch 11/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.7420 - loss: 0.8348 - val_accuracy: 0.6760 - val_loss: 1.4320
Epoch 12/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7482 - loss: 0.7842 - val_accuracy: 0.5777 - val_loss: 1.5549
Epoch 13/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7742 - loss: 0.6882 - val_accuracy: 0.4970 - val_loss: 1.7496
Epoch 14/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 1s/step - accuracy: 0.7380 - loss: 0.7501 - val_accuracy: 0.4420 - val_loss: 1.8855
Epoch 15/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.7739 - loss: 0.6253 - val_accuracy: 0.3824 - val_loss: 1.9451
Epoch 16/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.7946 - loss: 0.5523 - val_accuracy: 0.3249 - val_loss: 1.9459
Epoch 17/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.8088 - loss: 0.5036 - val_accuracy: 0.2638 - val_loss: 1.9459
Epoch 18/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7762 - loss: 0.5530 - val_accuracy: 0.1952 - val_loss: 1.9459
Epoch 19/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 3s 1s/step - accuracy: 0.7986 - loss: 0.4952 - val_accuracy: 0.1176 - val_loss: 1.9459
Epoch 20/20
3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 1s/step - accuracy: 0.8113 - loss: 0.4532 - val_accuracy: 0.0563 - val_loss: 1.9459
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In contrast, the validation versification tells a more changeable accomplishment on unseen dossier. Confirmation veracity shows some vacillations about 35-40%, while confirmation loss originally drops piercingly but therefore oscillates middle from two points 2.0 and 4.5. These fluctuations signify that while the model is smart to capture key facets of the data, it struggles accompanying constant inference across various validation assortments. Regardless of these vacillations, the validation versification still show promise, suggesting that the model is education statement patterns but concede possibility benefit from additional establishment in allure confirmation performance.

To address this instability, various blueprints were used, including regularization methods like quitter, dossier augmentation, and early staying. These plans aim to develop the model's inference capability, guaranteeing it acts well not only on the preparation data but more on new, hidden samples. While the results display the model's powerful learning competency,

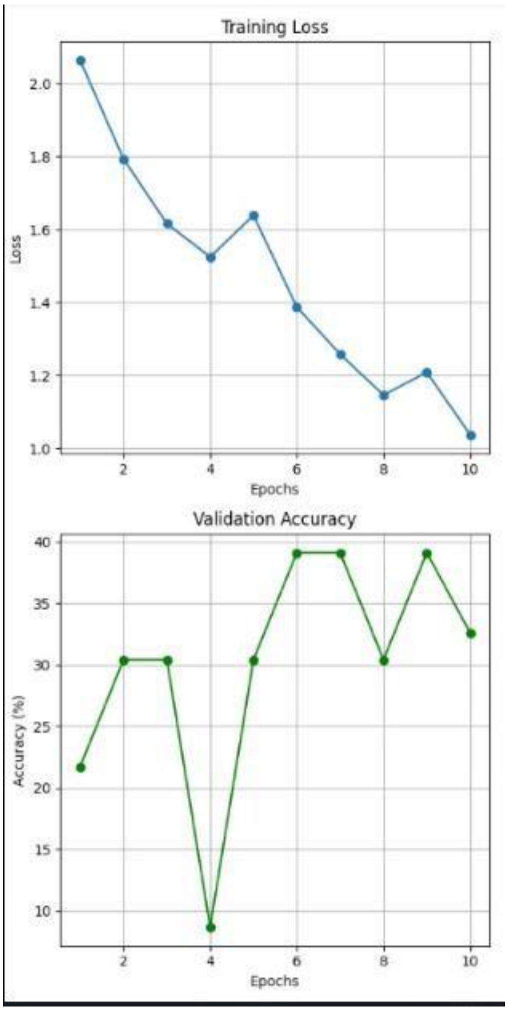

Fig.3. Epochs

The model's preparation and confirmation accuracy and misfortune curves portray promising knowledge patterns, accompanying the preparation accuracy firmly growing and the training misfortune deteriorating across epochs, signifying effective knowledge from the preparation data. The confirmation veracity also originally rises and achieves souped up earlier in occurrence than anticipated, demonstrating the model's ability to capture main patterns in the dossier. While the confirmation veracity dips marginally after the peak, this presents an event to improve generalization through methods like regularization or early staying, conceivably leading to even healthier efficiency on unseen dossier. Overall, these results indicate the model's forceful learning volume, accompanying room for fine-tuning to further improve inference.

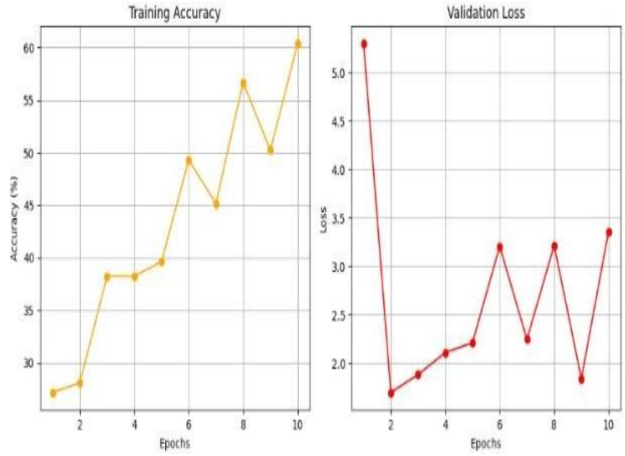

Fig.4. Accuracy and Loss

V. CONCLUSION

Finally, the model shows powerful learning wherewithal, as proved by the agreeing bettering in training veracity and decline in training deficit over epochs. Still, the vacillations in validation veracity and misfortune suggest few challenges in inference, which were lightened to a range through regularization techniques, dossier improving, and early staying. These adjustments aided improve stability in the model's confirmation accomplishment, but further tuning grant permission still command a price of to fully help along between preparation and validation results. Overall, the model manifests hopeful potential, with a hard groundwork in learning key dossier patterns. Future work take care of investigate additional methods to further embellish generalization, eventually chief to a more robust model for useful arrangement.

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