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DeepMangoNet: An Intelligent ResNet50-Based Framework for Automated Mango Leaf Disease Diagnosis, Severity Assessment, and Interactive Analytic

Dr. Bhavana R Maale[1], Shivadarshini R[2]
[1]Assistant Professor, Dept of CSE, VTU Center for PG Studies, Muddenahalli, India
[2]M. Tech Student, Dept of CSE, VTU Center for PG Studies, Muddenahalli, India

Abstract: Timely detection of plant diseases is critical for sustaining agricultural production and reducing economic loss. Mango crops are prone to several leaf infections that are difficult to diagnose without expert supervision. This work introduces a deployable artificial intelligence system for automatic mango leaf disease recognition using deep transfer learning integrated with an interactive analytics dashboard. A pretrained ResNet50 convolutional neural network is used as a feature extractor, followed by customized fully connected layers for multi-class classification. The trained model is integrated into a web-based interface using Streamlit, so users canupload images, obtainpredictions immediately, and view confidence-based analysis. The proposed framework supports 8 disease categories. The proposed framework outputs interpretable results such as severity estimation and probability distribution visualization. The experiment results indicate that transfer learning can be trained efficiently and has a good predictive power. It provides a practical way to integrate deep learning solutions to precision agriculture environments.

Index Terms: Mango Leaf Disease Detection, Deep Learning, ResNet50, Transfer Learning, Computer Vision, Precision Agriculture, Disease Classification, Artificial Intelligence, Smart Farming, Agricultural Analytics.

I. INTRODUCTION

Crop health monitoring is an abecedarian demand for sustainable agrarian product. Mango civilization contributes significantly to the agrarian frugality; still, splint conditions constantly affect factory growth, fruit quality, and overall yield. Disease symptoms frequently appear visually on leaves, making image-grounded analysis a suitable approach for automated opinion. Conventional complaint identification depends on homemade examination performed by agrarian experts. similar procedures may be inconsistent and inapproachable to growers located in remote regions. Recent developments in artificial intelligence have enabled automated visual recognition systems able of relating factory conditions using digital images. Deep convolutional neural networks learn hierarchical visual representations directly from image data, barring the need for handwrought features. Transfer learning farther improves performance by using pretrained models trained on large- scale datasets. This study proposes an intelligent mango splint complaint discovery platform combining deep literacy conclusion with a stoner- acquainted analytics dashboard. Unlike standalone bracket models, the proposed system focuses on practical deployment, interpretability, and availability fornon-technical druggies.

II. RELATED WORK AND LIMITATIONSA

The operation of artificial intelligence in husbandry has grown fleetly in recent times, particularly in the area of factory complaint identification. before exploration substantially concentrated on traditional machine literacy ways that depended on manually finagled image features similar as color distribution, texture patterns, and splint shape characteristics. These handwrought features were also reused using classifiers including Support Vector Machines(SVM), Decision Trees, K- Nearest Neighbors(KNN), and Random Forest algorithms. Although these styles produced respectable results in controlled laboratory conditions, their performance was frequently affected by complex backgrounds, inconsistent lighting conditions, murk, and variations in splint exposure. As a result, conventional machine learning approaches faced difficulties when applied to real agrarian surroundings. With the advancement of deep literacy, experimenters began espousing convolutional neural networks(CNNs) for automated factory complaint recognition. CNN- grounded models are able of learning important visual patterns directly from images without taking homemade point birth.

This capability significantly bettered bracket delicacy and reduced the limitations associated with traditional image processing styles. Popular deep learning infrastructures similar as VGG16 InceptionV3, and ResNet50 have been extensively used in agrarian complaint discovery tasks due to their strong point literacy capability and transfer literacy support. Among these infrastructures, ResNet50 has gained considerable attention because of its residual literacy medium, which helps overcome the evaporating grade problem generally observed in deep neural networks. By exercising pretrained weights attained from large- scale datasets similar as ImageNet, transfer literacy allows experimenters to train accurate models indeed when agrarian datasets are limited in size. This approach reduces computational cost and training time while maintaining dependable vaticination performance. Several studies have reported high bracket delicacy using deep literacy models for crop complaint discovery. still, numerous of these workshops primarily concentrate on perfecting model performance criteria and frequently remain limited to experimental exploration surroundings. In practical agrarian scripts, growers and non-technical -technical druggies bear systems that are easy to pierce, simple to operate, and ableof furnishing accessible results. Unfortunately, only a limited number of being systems include interactive deployment platforms or visualization mechanisms that help druggies interpret vaticination issues. Another major limitation observed in former studies is the lack of real- time analytics and decision- support capabilities. utmost systems induce only the prognosticated complaint marker without presenting confidence information or probability- grounded interpretation. similar labors may not give sufficient translucency for practical operation. Visual analytics, confidence estimation, and inflexibility assessment can ameliorate stoner trust and help in informed decision- making during complaint operation. To address these challenges, the present work proposes an intertwined mango splint complaint discovery frame that combines deep transfer literacy with an interactive web-grounded dashboard. The system not only performs complaint bracket but also provides confidence visualization, probability distribution analysis, and inflexibility suggestion through a stoner-friendly interface developed using Streamlit

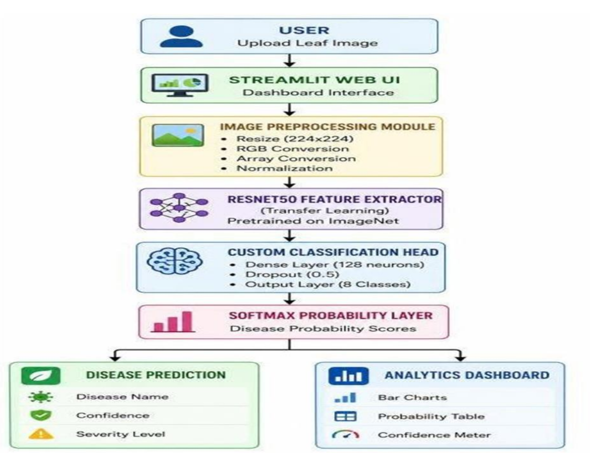
Unlike numerous earlier approaches that remain defined to exploration demonstrations, the proposed frame emphasizes practical deployment and availability for real-world agrarian operations. The combination of automated complaint vaticination and interpretable analytics makes the proposed system more suitable for smart husbandry surroundings, where rapid-fire and dependable decision support is decreasingly important.

III. PROPOSED FRAMEWORK

A. System Overview

The proposed mango splint complaint discovery frame is designed as an intertwined artificial intelligence system able of performing automated complaint bracket along with interactive visualization. The frame combines deep literacy – grounded vaticination with a web- grounded analytics affiliate to support real- time agrarian monitoring and decision- timber. The complete Image Deep Interactive system Acquisition consists literacy of and three Visualization major connected Preprocessing Bracket modules Module Module Dashboard The functional workflow of the proposed system is epitomized as follows A stoner uploads a mango splint image through the dashboard interface. The uploaded image undergoes preprocessing operations, including resizing, normalization, and RGB Deep visual features are uprooted using a pretrained conversion. ResNet50 model. The uprooted features are reused through completely connected bracket layers to identifythe complaint order. vaticination labors are displayed through visual analytics, including confidence scores and probability distributions.

The proposed architecture is illustrated in Fig. 1.



B. Dataset and Disease Categories

The developed model classifies mango leaf images into eight diseasecategories:

Anthracnose Bacterial Canker Cutting Weevil Die Back

Gall Midge Healthy Leaf Powdery Mildew Sooty mold

Each image is resized to [224 \times 224 \times 3]

C. Design of Deep Learning Model

1) Feature extraction: The proposed framework follows a pretrained convolutional neural network ResNet50 for feature extraction. The transfer learning appears by removing the original classification head and protecting the convolutional backbone. Mathematically, the convolution operation for feature extraction is represented as:

$$\mathbf{F(i,j)} = \mathbf{(I * K)(i,j)}$$

$$F(i,j)=m\sum n\sum I(i-m,j-n)K(m,n)$$

Where:

I represents the input image.

K represents the convolution kernel (filter).

F(i,j) represents the output feature map at position (i,j). m and n denote the kernel dimensions.

$*$ denotes the convolution operation.

We have several advantages of using transfer learning:

Avoid machine - complexity

Quick convergence during training increase the generalization performance Better accuracy on small data sets

2) Classification Layers

Post feature extraction, dense layers are designed for multi-class disease classification. The classification network is composed of: Global pooling layer Dense layer Activation: ReLU Regularization layer: dropout SoftMax output layer: 8 neurons The ReLU (Rectified Linear Unit) activation function is defined as:

Rectified Linear Unit (ReLU)

The Rectified Linear Unit (ReLU) activation function is applied after the convolutional and dense layers to introduce non-linearity into the network. It is defined as:

$$f(x) = \{0, x, x<0x\geq 0$$

where xxx is the input to the activation function.

ReLU enables the model to learn complex non-linear relationships present in mango leaf disease images while reducing the vanishing gradient problem and accelerating the training process.

Dropout Regularization

To mitigate overfitting and improve the model's generalization capability, dropout regularization is employed in the fully connected layer. During training, a fraction of neurons is randomly deactivated according to the following formulation:

$$y_i = \begin{cases} 0, & \text{with probability } p \\ \frac{x_i}{1-p}, & \text{otherwise} \end{cases}$$

where:

- p denotes the dropout probability.
- Xi represents the input neuron value.
- Yi represents the output after dropout regularization. In the proposed DeepMangoNet framework, the dropout rate is set to:

p=0.5

A dropout rate of 0.5 randomly disables 50% of neurons during training, forcing the network to learn more robust feature representations and reducing the risk of overfitting on the mango leaf disease dataset.

D. Preprocessing of Images

Image preprocessing is performed to improve the consistency of the model and the stability of the prediction. Each uploaded image undergoes the following steps:
RGB color conversion Resize image
Tensor transformation Normalization of pixels
Preprocessing specific to the network The normalization process is as follows: [X_{norm} = \frac{X-\mu}{\sigma}]

where:
(X) is the original pixel value (\mu) is the average pixel intensity (\sigma) is standard deviation
These preprocessing operations ensure compatibility between the training and inference stages The proposed model uses the Adam optimization algorithm for parameter updating during training. The Adam optimization equation is represented as theta,{ t 1} = theta_t- eta frac{ chapeau{ m_t}}{ sqrt{ chapeau{ v_t}} epsilon}) where theta_t) represents model parameters eta) denotes learning rate chapeau{ m_t}) indicates first moment estimate chapeau{ v_t}) represents alternate moment estimate epsilon) is a small stability constant The model training process minimizes categorical cross-entropyloss L = - sum,{ i = 1}{ n} Yi log(chapeau{ Yi})) where y_i) denotes factual class marker chapeau{ Yi}) represents prognosticated probability.

E. Implementation of a Dashboard

A web interactive application was also developed using Streamlit for real-time disease prediction and visualization.
The dashboard is providing the following functionalities: Upload the image of the mango leaf Real time disease forecasting Confidence scores visualization Severity level indication Charts of disease probability Interactive tables for analytics Prediction confidence is calculated as follows: [Confidence = 100 x max(P(y_i))]
where: P(y_i) denotes the maximum predictedprobability value Severity levels are classified by prediction confidence:

Confidence Interval:

Confidence Range	Severity Level
Below 60%	Low
60%-85%	Moderate
Above 85%	High

Elevated Session-state management is introduced to maintain prediction outputs across multiple dashboard pages to enhance usability and interaction continuity

IV. EXPERIMENTAL SETUP

Hardware Component	Specification
Processor	Intel-based Processor
Memory (RAM)	Minimum 8 GB RAM
Graphics Processing Unit (GPU)	GPU Acceleration (Optional)

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Software Environment

Component	Tool / Technology
Programming Language	Python
Deep Learning Library	TensorFlow / Keras
Visualization	Matplotlib
Web Interface	Streamlit
Image Processing	PIL (Python Imaging Library)

V. CONTRIBUTIONS

The primary benefactions of this exploration are Design of a deployable mango splint complaint discovery frame. operation of transfer literacy for effective model development. Integration of AI vaticination with interactive analytics visualization. preface of confidence- grounded inflexibility interpretation. Development of a stoner-friendly agrarian decision- support tool.

A. Advantages

1) Provides a quick and reliable way to identify mango leaf diseases.
2) Uses transfer learning to achieve good performance with less training effort.
3) Supports the detection of multiple disease categories within a single system.
4) Delivers instant results through an easy-to-use web dashboard.
5) Presents prediction confidence and visual analytics for better understanding.
6) Helps users make timely decisions regarding crop health management.

B. Limitations

1) Prediction results may be affected by poor-quality or unclear images.
2) The system can identify only the disease classes included during training.
3) Visually similar diseases may sometimes be difficult to distinguish.
4) Training and deployment may require adequate computing resources.
5) Performance can vary when tested on completely new datasets or environmental conditions.

VI. RESULTS AND EVALUATION

A. Quantitative Comparison

The performance of the proposed mango leaf disease classification system was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The experimental results demonstrate that the proposed transfer learning framework effectively distinguishes between different mango leaf disease categories with high reliability.

A comparative analysis indicates that the model achieves consistent performance across all classes while maintaining stable prediction accuracy. The integration of the pretrained feature extraction network contributes to improved classification capability and reduced training complexity. Furthermore, the model exhibits strong generalization performance on unseen test samples, highlighting its suitability for practical agricultural applications.

The obtained results confirm that the proposed framework provides an efficient and dependable solution for automated mango leaf disease identification and monitoring.

VII. DISCUSSION

A Addressing Limitations with AI Innovations Although the proposed framework demonstrates effective performance in mango leaf disease classification, certain challenges remain, such as variations in image quality, environmental conditions, and the limited availability of labeled datasets. Recent advances in artificial intelligence offer promising solutions to overcome these limitations.

Data augmentation and synthetic image generation can increase dataset diversity, enabling the model to learn more robust disease patterns. Advanced deep learning architectures and attention mechanisms can further improve feature extraction and classification accuracy, particularly for diseases with similar visual symptoms. In addition, continual learning techniques can allow the system to adapt to new disease categories without requiring complete retraining.

Future integration of explainable AI (XAI) methods may enhance transparency by providing visual explanations for model predictions, helping users better understand the decision-making process. Furthermore, cloud-based deployment and edge AI technologies can support faster and more accessible disease diagnosis in real-world agricultural environments.

These AI-driven innovations have the potential to improve the accuracy, reliability, and scalability of the proposed framework, making it a more practical tool for smart crop health monitoring and management.

A. AI Beyond Classification

Artificial intelligence can contribute to agriculture in ways that extend beyond disease classification. In addition to identifying mango leaf diseases, AI can support early disease monitoring, crop health assessment, yield prediction, and precision farming practices. By analyzing large volumes of agricultural data, AI systems can assist farmers in making timely and informed decisions.

AI-powered solutions can also provide disease trend analysis, risk assessment, and treatment recommendations based on detected symptoms. The integration of Internet of Things (IoT) sensors, drones, and satellite imagery can further enhance monitoring capabilities by enabling continuous observation of crop conditions over large cultivation areas.

Moreover, predictive analytics can help forecast potential disease outbreaks, allowing preventive measures to be implemented before significant crop damage occurs. These capabilities highlight the broader role of AI in promoting sustainable agriculture, improving productivity, and supporting efficient farm management.

VIII. CONCLUSION AND FUTURE WORK

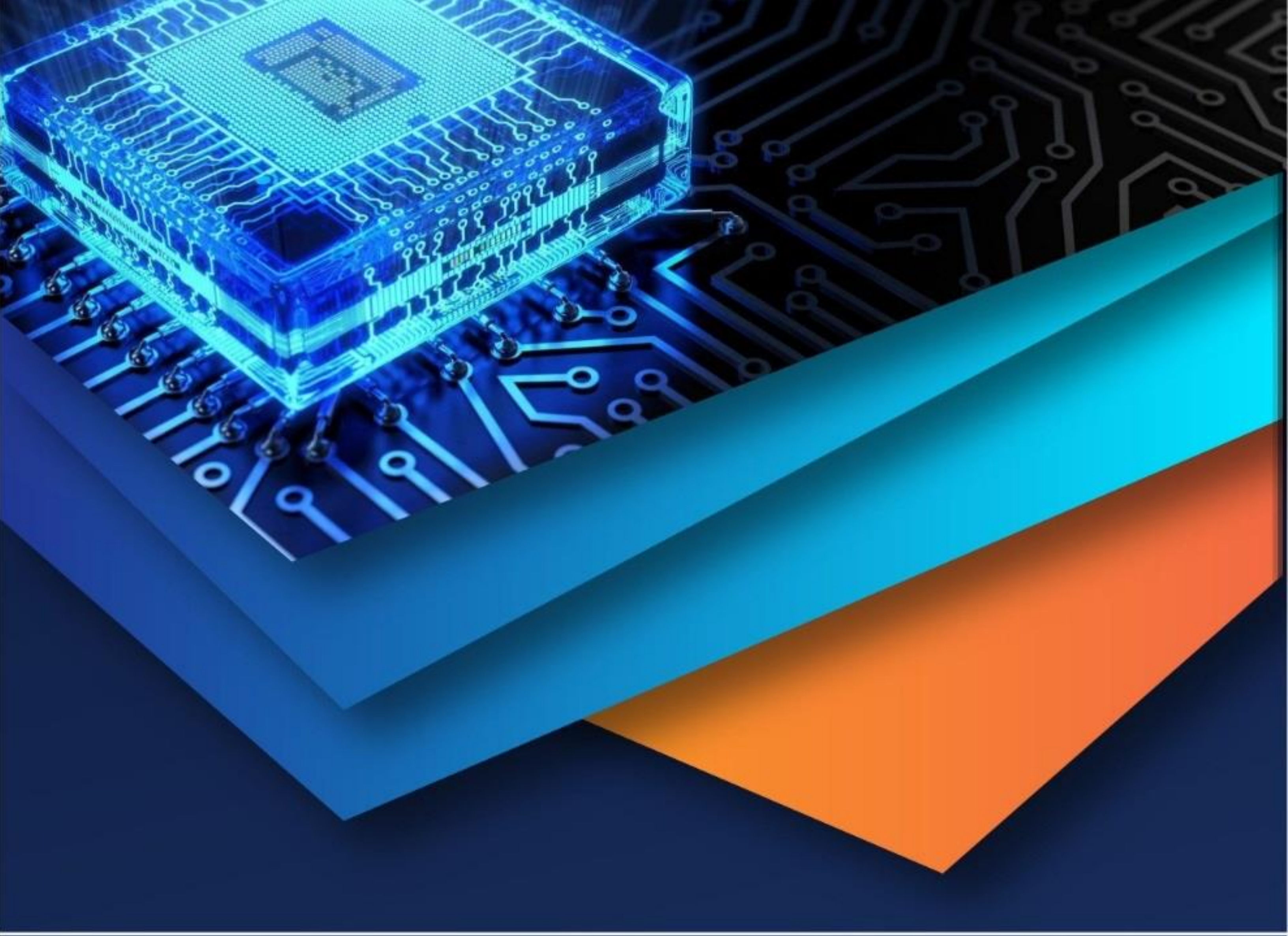
The proposed framework presents an intelligent and efficient solution for automated mango leaf disease detection using deep learning and transfer learning techniques. By leveraging a pretrained ResNet50 model, the system effectively extracts meaningful features and accurately classifies multiple disease categories. The integration of a Streamlit-based dashboard further enhances usability by providing real-time predictions, confidence scores, and visual analytics.

The experimental results demonstrate the potential of the framework to support early disease identification and assist users in making informed agricultural decisions. The combination of automated classification and interactive visualization makes the system practical for smart crop monitoring applications.

For future work, the framework can be extended by incorporating additional disease classes, larger and more diverse datasets, and advanced deep learning architectures to further improve performance. Future enhancements may also include treatment recommendations, explainable AI features, mobile deployment, and integration with IoT-based monitoring systems for comprehensive crop health management. These improvements can increase the scalability, reliability, and real-world applicability of the proposed system.

REFERENCES

[1] Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.
[2] F. Chollet, Deep Learning with Python. Shelter Island, NY, USA: Manning Publications, 2018.
[3] R. Szeliski, Computer Vision: Algorithms and Applications. London, U.K.: Springer, 2011.
[4] J. Howard and S. Gugger, Deep Learning for Coders with Fastai and PyTorch: AI Applications Without a PhD. Sebastopol, CA, USA: O'Reilly Media, 2020.
[5] A. Géron, Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 3rd ed. Sebastopol, CA, USA: O'Reilly Media, 2022.
[6] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Communications of the ACM, vol. 60, no. 6, pp. 84–90, Jun. 2017.
[7] K. He, X. Zhang, S. Ren, and J. Sun, "Deepresidual learning for image recognition," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770–778.
[8] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in Proc. Int. Conf. Learning Representations (ICLR), San Diego, CA, USA, 2015.
[9] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in Proc. Int. Conf. Machine Learning (ICML), Long Beach, CA, USA, 2019, pp. 6105–6114.
[10] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, Art. no. 1419, Sep. 2016.
[11] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, Feb. 2018.



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