Disease Identification & Classification in Millet Crops Using ML Techniques

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Abstract: Millets, including pearl, finger, and sorghum varieties, are essential crops known for their adaptability to harsh conditions and significant contribution to food security. However, their cultivation is frequently disrupted by plant diseases and weed infestations, which affect yield and quality. Traditional methods of addressing these issues often require manual effort and are limited in scalability, making them inefficient for large-scale farming. This project aims to provide a comprehensive solution through Machine Learning (ML) and Computer Vision technologies. Using the pre-trained VGG16 model, the system identifies and classifies diseases in millet crops, determining whether the plants are healthy or affected by specific conditions such as rust, mildew, or blast. Additionally, a weed detection feature is incorporated to facilitate effective management of weeds. The solution is deployed as a user-friendly application designed to deliver real-time insights, improving agricultural practices and promoting sustainable millet farming.

1 INTRODUCTION

1.1 Significance of Millets

Millets are resilient and nutritious crops, widely cultivated in regions where other staples struggle to grow. Pearl, finger, and sorghum millets, in particular, provide essential nutrients and are critical to addressing food security challenges. They are also environmentally sustainable, requiring minimal water and chemical inputs.

1.2 Challenges in Millet Cultivation

Despite their resilience, millets are not immune to agricultural challenges. Two primary issues impacting millet productivity are:

- **Diseases:** Common diseases such as rust, smut, and blast can severely affect millet growth, resulting in reduced yields.
- **Weed Infestation:** Weeds compete with crops for essential resources like sunlight, water, and nutrients, further reducing productivity.

1.3 Drawbacks of Current Practices

Farmers traditionally rely on manual inspection for disease and weed management. This technique has drawbacks such as: -

- Being time-intensive and unsuitable for large-scale farming.
- Prone to errors and inconsistencies.
- Inability to provide timely interventions for early-stage disease or weed management.

1.4 Role of Technology

The integration of ML and Computer Vision in agriculture presents an opportunity to address these challenges efficiently. Pre-trained models such as VGG16 enable quick and precise identification of diseases and weeds, allowing for automated solutions tailored to millet cultivation. Table shows the proposed Diseases.

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Table 1: Proposed Diseases.

<table>
<tr><th>S No.</th><th>Title</th><th>Year</th><th>Author</th><th colspan="6">Diseases</th><th>Proposed Diseases</th></tr>
<tr><td>1.</td><td>Deep-millet: a deep learning model for pearl millet disease identification to envisage precision agriculture</td><td>2024</td><td>Jhonson et al</td><td colspan="2">Rust Disease</td><td colspan="2">Blast Disease</td><td colspan="2">Powdery Mildew</td><td rowspan="3">→ Downy Mildew
→ Blast Disease
→ Rust Disease</td></tr>
<tr><td>2.</td><td>A Smart and sustainable framework for millet crop monitoring equipped with disease detection using enhanced predictive intelligence</td><td>2023</td><td>Mishra et al</td><td colspan="3">Blast Disease</td><td colspan="3">Rust Disease</td></tr>
<tr><td>3.</td><td>IoT and Interpretable Machine Learning Based Framework for Disease Prediction in Pearl Millet</td><td>2021</td><td>Nidhi Kundu et al</td><td colspan="3">Blast Disease</td><td colspan="3">Rust Disease</td></tr>
</table>

2 LITERATURE SURVEY

In (I Johnson, 2024), The paper presents the Deep Millet model, a CNN-based solution for detecting pearl millet diseases with 98.86% accuracy, enabling real-time disease identification through a mobile app to support precision agriculture. (Johnson et al, 2022). In (Mohamed Salama, 2024), Agriculture faces threats from pests and diseases. This paper reviews AI's role in automating detection, noting its efficiency and accuracy. It discusses implementation challenges and solutions, and calls for ongoing research to enhance AI in pest and disease management. (Salama et al, 2024). In (Nivargi Anil Basavant, 2024), The paper presents a machine learning-based agricultural system for disease classification, crop prediction, and fertilizer recommendation. It helps optimize farming practices, improve productivity, and promote sustainability. Future enhancements aim to refine algorithms and integrate real-time data for broader adoption. Basavant et al, 2024).

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In (K. Sai Susheel et al,2023), This review explores intelligent techniques like machine learning, image processing, & IoT in identifying, monitoring, & managing crop pests & diseases, aiming to enhance agricultural productivity and sustainability. This review includes different crops & diseases. Susheel et al, (2023). In (Sushruta Mishra et al,2023), The paper proposes a smart millet crop monitoring system using IoT and a Customized CNN, achieving 98.8%

accuracy in disease detection to support farmers and enhance yield. Mishra et al, (2023). In (Riya Walia et al., 2023), The paper addresses sugarcane's susceptibility to Top Borer disease and introduces an AI system using CNNs and high-resolution images for precise detection. It advocates sustainable farming and highlights the need for ongoing updates to tackle emerging challenges. Walia et al, (2023). In (Md. Mehedi Hasan et al., 2023), The document discusses machine learning and image processing techniques for detecting rice diseases, focusing on their role in improving accuracy and boosting agricultural productivity. Hasan et al, (2023).

In (Wanjie Feng et al., 2024), This paper shows how AI models like SoyDNGP are changing crop breeding by helping predict plant traits, choose the best parent plants, and blend genetic and environmental data to grow better crops faster. Feng et al, (2024). In (Bita Parga Zen et al., 2022), This study will discuss the implementation of Artificial Intelligence-based plant disease detection software. At this stage, deep learning models are created using cameras matched. Zen et al, (2022). In (Md. Ashraful Haque, et al,2022), The paper presents a deep learning-based approach for identifying three major maize diseases using in-field images. It applies an Inception-v3 CNN model, achieving a classification accuracy of 95.99%. The approach demonstrates improved disease detection performance, even with varied backgrounds and enhanced brightness conditions. Haque et al, (2022).

In (Tiago Domingues, et al., 2022), The paper reviews machine learning techniques for detecting, classifying, and predicting crop diseases and pests. It emphasizes the potential of ML in sustainable farming, using weather, image, and spectral data to improve crop yield and reduce pesticide use. (Dominques et al, 2022). In (Sana Akbar, et al., 2022), The study integrates IoT and machine learning for wheat disease detection, using MobileNet and EfficientNet-B3. Techniques include image preprocessing, augmentation, and CNN-based classification, emphasizing IoT's role in monitoring and improving crop yield management. Akbar et al, (2022).

In (Nidhi Kundu, et al., 2021), The shift to high-yield grains has worsened malnutrition, prompting India to promote millets as "Nutri Cereals" for food security. This paper proposes using machine learning and IoT for automated disease detection in pearl millet. (Kundu et al,2021). In (Muhammad Hammad Saleem, et al., 2019), The paper reviews the application of deep learning (DL) techniques for detecting and classifying plant development of a fuzzy expert system for integrated disease management in finger millet crops, leveraging fuzzy logic to diagnose diseases and recommend control measures for effective crop management. Roseline et al, (2012).

3 METHODOLOGY

The project follows a structured approach divided into three key modules:

- Disease Detection: Identifying whether millet crops (Pearl, Finger, Sorghum) are healthy or diseased.
- Disease Classification: Categorizing diseases like Rust, Smut, or Blast.
- Weed Detection: Differentiating crops from weeds for better yield management.

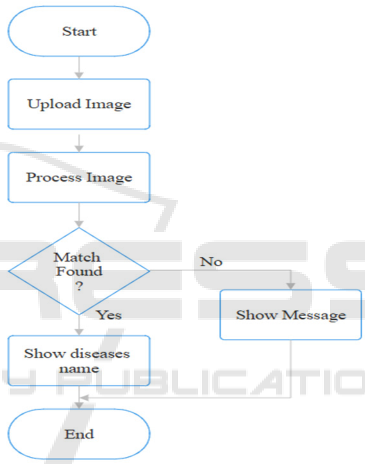

Figure 1: Disease Detection.

As shown if figure 1 The Disease Detection Module follows a systematic approach, starting with data collection from public datasets, field surveys, and research institutions. Images are labeled as healthy or diseased (Rust, Smut, Blast). In data preparation, preprocessing (resizing, normalization, noise reduction) and augmentation (rotation, flipping, brightness adjustment) enhance model performance. The disease detection phase employs VGG16 fine-tuning and custom CNN models for better accuracy. Model training uses Categorical Cross-Entropy loss, the Adam optimizer, and dynamic learning rate scheduling, with data split into training, validation, and test sets. Evaluation relies on accuracy, precision, recall, F1-score, and k-fold cross-validation. The workflow includes image collection, preprocessing, disease detection, prediction, and result output with diagnosis and treatment recommendations.

As shown if figure 2 below the Disease Classification Module categorizes millet diseases (Leaf Spot, Rust, Downy Mildew, Blight) using crop images. It involves dataset collection, pre-processing (resizing, normalization, augmentation), and model selection (pre-trained CNNs like ResNet, VGG16, or custom models). Feature extraction captures color, texture, and edge patterns. Model training optimizes performance using categorical cross-entropy and the Adam optimizer, while evaluation relies on accuracy, precision, recall, and F1-score. Post-processing assigns labels based on probability thresholds and visualizes results. The workflow follows dataset collection, preprocessing, model selection, training, evaluation, and result visualization for accurate disease identification.

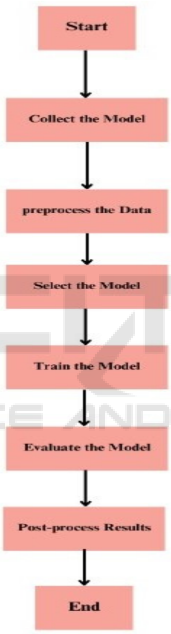

Figure 2: Disease Classification.

As shown if figure 3 The Weed Detection Module automates weed identification in Pearl millet, Finger millet, and Sorghum millet fields, improving crop management. It collects images from drones, smartphones, and cameras, supplemented with open-source datasets. Preprocessing includes resizing (224x224 pixels), noise reduction, brightness adjustments, and data augmentation. The system uses U-Net/Mask R-CNN for segmentation and CNN models like ResNet, MobileNet for classification, with transfer learning for better accuracy. The dataset is split (70% training, 20% validation, 10% testing), optimized using Adam, and evaluated with IoU, Dice Coefficient, Precision, Recall, and F1-Score.

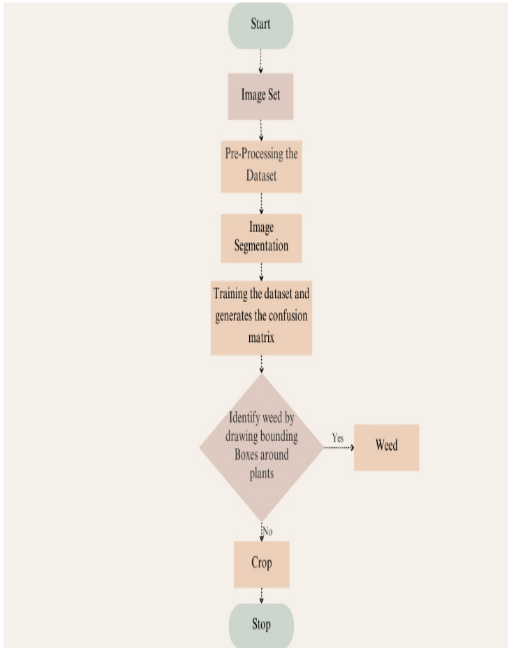

Figure 3: Weed Detection.

3.1 Components

3.1.1 Image Acquisition & Preprocessing

Components Used:

- Digital Camera / Smartphone / Web Scraping (for collecting images).
- Image Dataset (124 images of diseased & healthy millet).
- OpenCV / PIL (for image processing).

Functions:

- Capture and store images of healthy and diseased millet crops.
- Resize images to 150×150 px for input into the CNN.
- Convert images to RGB format if required.

3.1.2 Data Augmentation

Components Used:

- Keras Image Data Generator
- NumPy, OpenCV

Techniques Applied:

- Rotation (Randomly rotating images).

- Flipping (Horizontal & Vertical).
- Zooming (Rescaling images).
- Brightness Variation (Simulating real-world lighting).

Purpose:

- Increase dataset size (from 124 to **711** images).
- Reduce overfitting.

3.1.3 Transfer Learning with VGG16

Components Used:

- VGG16 Pre-Trained Model (Keras / TensorFlow)
- Feature Extraction Layers (Convolutional & Pooling layers).

Function:

- Freeze the initial layers of VGG16 to retain learned features.
- Extract features from input images to detect disease patterns.

3.1.4 Fully Connected Layers (Custom Classification Head)

Components Used:

- Dense Layers (Fully Connected Layers)
- Dropout Layer (To prevent overfitting)
- Activation Functions: ReLU & Sigmoid

Structure:

- Two fully connected layers added on top of VGG16**.**
- Final Layer: Sigmoid Activation → Binary Classification (Healthy / Diseased).

3.1.5 Model Training & Optimization

Components Used:

- Optimizer: Stochastic Gradient Descent (SGD) with Momentum (0.9)
- Loss Function: Binary Crossentropy
- Early Stopping (To prevent overfitting).
- 80-20 Split (Training & Validation)**.**

Training Configuration:

- Learning Rate: 1e-4
- Epochs: 30 (Early stopping applied).

3.1.6 Disease Classification & Prediction

Components Used:

- Trained CNN Model
- Softmax / Sigmoid Activation for Classification
- Performance Metrics: Accuracy, Precision, Recall, F1-Score

Function:

- Input: New millet leaf image.
- Processing: Feature extraction & classification.
- Output: Healthy or Mildew-Affected (with 95% accuracy**).**

4 FUTURE SCOPE

- The future of this model holds great potential for smart agriculture. It can be expanded to detect multiple diseases in millet crops like finger millet, sorghum, and foxtail millet, as well as wheat, rice, and maize.
- Integrating it into mobile apps and IoT devices will allow farmers to snap pictures for instant disease detection, making it accessible and affordable.
- Using advanced deep learning models like Efficient Net and Vision Transformers will improve accuracy, while segmentation techniques (U-Net, Mask R-CNN) can help classify disease severity.
- Drones and remote sensing can be used for large-scale farm monitoring, optimizing pesticide use and resource management.
- Adding multi-language support will make it easier for farmers worldwide, and fine-tuning for regional diseases will improve effectiveness.
- This AI-driven approach will help farmers detect diseases early, boost crop yields, and ensure sustainability, ultimately contributing to global food security.

5 CONCLUSIONS

This project offers an integrated solution for millet farming by combining disease detection and weed identification into a single platform. Leveraging VGG16 and state-of-the-art ML techniques ensures high accuracy and efficiency, addressing the limitations of traditional methods. The deployable system promises to enhance millet productivity, reduce losses, and promote sustainable farming practices. Future work could include extending the model to additional crops and incorporating IoT-based monitoring for continuous field data collection.

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