AI-Driven Crop Infection Detection and Smart Herbicide Recommendation System

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ABSTRACT

Emotion detection is a crucial aspect of enhancing human-computer interaction, enabling systems to understand and respond to human emotions effectively. This study presents a deep learning-based multimodal emotion detection model that integrates speech recognition and facial expression analysis to achieve improved emotion classification accuracy. The proposed model leverages Convolutional Neural Network (CNN) architectures to process audio signals and facial images simultaneously, enhancing the system's ability to capture complementary information from both modalities. Existing approaches primarily employ Random Forest Classifier (RFC) and Deep Neural Network (DNN) models for emotion detection. However, these methods are limited in their ability to extract high-level spatial and temporal features effectively, resulting in suboptimal performance for complex multimodal datasets. In the proposed framework, a Deep Learning Convolutional Neural Network (DLCNN) architecture is employed to extract robust features from speech and facial images. These features are fused using a hybrid feature fusion technique, improving the model's robustness and accuracy. The integrated model is trained and evaluated on publicly available multimodal emotion datasets. Experimental results demonstrate that the proposed DLCNN-based approach achieves superior performance compared to existing methods, with significant improvements in accuracy, precision, recall, and F1-score. The novel approach offers a promising solution for real-time multimodal emotion detection, with potential applications in areas such as human-computer interaction, healthcare monitoring, surveillance systems, and personalized recommendation systems.

Keywords: Crop Disease Classification, Multi-Crop Diagnosis, Smart Farming, AgriTech, Leaf Image Analysis

1. INTRODUCTION

The history of multi-crop disease classification and pesticide recommendation systems can be traced to the intersection of agriculture and emerging technologies. In the late 20th century, early attempts to automate disease detection focused on basic rule-based systems. However, the true revolution came with the integration of machine learning in the early 21st century. As computer vision and image recognition technologies advanced, researchers began applying these tools to agricultural images, enabling more accurate and efficient identification of crop diseases. This laid the foundation for multi-crop disease classification systems, which could analyze images from various crops and distinguish between healthy and infected plants. Simultaneously, the development of pesticide recommendation systems gained momentum. Initially, these systems relied on expert knowledge and predefined rules. However, with the rise of machine learning algorithms and access to vast datasets, these systems evolved to incorporate dynamic factors such as weather conditions, soil health, and historical disease patterns. Deep learning models, particularly convolutional neural networks (CNNs) in computer vision applications, enhance the precision of crop disease detection. By learning intricate patterns and features within images, these models can distinguish between healthy and infected plants across various crops. Prior to the advent of computing technology, agricultural scientists relied on manual observation, experimentation, and domain knowledge to identify crop diseases and recommend treatments.

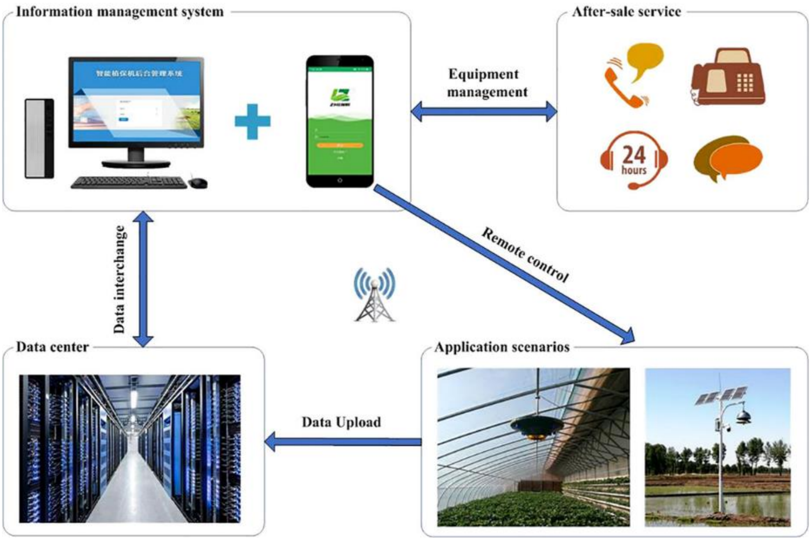


Fig 1: Multi crop disease detection and pest recommmnedation

The understanding of plant diseases dates back centuries, with early efforts focused on documenting symptoms, identifying pathogens, and developing rudimentary treatments. Agricultural extension services and research institutions played a crucial role in disseminating knowledge about crop diseases and management practices to farmers. The development of computing technology in the mid-20th century provided new tools for data analysis, modelling, and decision support in agriculture. Early computer-based agricultural systems focused on basic tasks such as data management, weather forecasting, and crop yield estimation. The 1980s saw the emergence of expert systems in agriculture, including disease diagnosis and management. Expert systems were rule-based computer programs that encoded domain-specific knowledge provided by agricultural experts. The systems helped farmers and agricultural professionals make informed decisions about disease identification, treatment selection, and pest management.

2. LITERATURE SURVEY

G. K. Srikanth, et al. [1] proposed a method in the abstract involves an integrated and collaborative platform for automated disease diagnosis, tracking, and forecasting in the context of plant diseases. Here are the key components of the proposed approach In recent years, there has been a significant shift towards leveraging advanced technologies like deep learning for predictive modeling in agriculture. One such approach involves utilizing environmental data pertaining to crop growth to develop predictive models for disease and pest infestations. Maheng, et al. [2] proposed a method for crop disease detection and pest prediction, based on AI and deep learning, involves the following key aspects:through the application of deep convolutional neural networks (CNNs), researchers have achieved an impressive accuracy rate of 99.35% in identified 14 crop species and 26 diseases from controlled leaf images. This breakthrough not only surpasses the capabilities of traditional methods but also addresses critical challenges such as labour costs, accuracy, and environmental impact. Despite these advancements, challenges persist, including data-intensive tasks, processing time, and storage limitations associated with deep learning approaches. Venkata saichandrakanth.p,et al. [3] proposed a method for pest detection and classification using deep learning involves the following key aspects like

Looking ahead, the integration of artificial intelligence (AI) and deep learning holds tremendous promise for revolutionizing crop disease management and prevention, ushering in an era of more efficient, accurate, and sustainable agricultural practices." Ramya N, et al. [4] proposed a method for plant disease detection using deep learning involves the following key aspects agricultural technology advancements, deep convolutional neural networks (CNNs) play a pivotal role. These sophisticated algorithms excel in swiftly recognizing disease indications and symptoms from plant leaves and stems, thereby facilitating the promotion of healthy crop growth. Additionally, employing pre-trained deep learning. Tirkey,et al. [5] proposed a method utilizes deep learning, specifically YoloV5, InceptionV3, and CNN models, for real-time identification and detection of insects in Soybean crops. Achieving high accuracies of 98.75%, 97%, and 97% respectively, the YoloV5 algorithm stands out for its exceptional speed at 53fps, making it suitable for efficient real-time insect detection. The study aims to streamline agriculture practices by reducing the workload of producers through a simplified yet effective solution. Ramanjot ,et al. [6] proposed a method for plant disease detection in India, focusing on data sources, pre-processing, feature extraction, data augmentation, and model selection. A comprehensive analysis of 182 papers from 2010 to 2022 identifies 75 relevant works, providing a valuable resource for researchers aiming to enhance system performance and accuracy in plant disease identification through data-driven approaches. Ma L, et al. [7] introduced CTR_YOLOv5n, has been improved YOLOv5n model for detecting common maize diseases (leaf spot, gray spot, and rust) in mobile applications. The model incorporates a Coordinate Attention (CA) mechanism and a Swin Transformer (STR) detection head (TR2), enhancing accuracy by 2.8% compared to the original model while significantly reducing memory size to 5.1MB, meeting lightweight requirements for mobile use. Shoaib M, et al. [8] explored the application of Machine Learning (ML) and Deep Learning (DL) techniques for early identification of plant diseases, addressing the limitations of manual detection methods. Focusing on advancements between 2015 and 2022, the study emphasizes improved accuracy and efficiency in plant disease detection through experimental validation. Guerrero A , et al. [9] Tproposed a Convolutional Neural Network (CNN)-based model for identifying and classifying tomato leaf diseases in Mexico. Utilizing a public dataset and additional field photographs, the model incorporates generative adversarial networks to mitigate overfitting. Ahmed I, et al. [10] presented an automated method for early detection of plant diseases on large crop farms using machine learning and deep learning techniques. Utilized the "Plant Village" dataset with 17 diseases across 12 crop species, the study employs support vector machines (SVMs). Balaji V, et al. [11] conducted a thorough survey of methodologies for detecting rice plant diseases, analyzed various classifiers and strategies employed in studies from the last decade. It proposed a model for rice disease detection utilizing an enhanced convolutional neural network (CNN) to leverage the success of deep neural networks in image classification challenges. Kirola M, et al. [12] proposed a comprehensive framework for plant disease detection and classification based on leaf symptoms, used machine learning and deep learning techniques. Image acquisition, pre-processing, segmentation, feature extraction, and classification are incorporated in the disease detection method. S. C. Gopi, et al. [13] proposed utilizing transfer learning models, specifically examining frozen layers and fine-tuning, for automated detection of rice leaf diseases. DenseNet169 with frozen layers achieves a notable testing accuracy of 99.66%, while as a fine-tuned transfer learning model, outperforms with an impressive testing accuracy of 99.99%. Kumar R, et al. [14] reviewed recent research on fungal and bacterial plant disease detection, focused on computer vision-based techniques. It categorized approaches into machine learning and deep learning, highlighting the utilization of real-field and laboratory-conditioned plant leaf images. Chen J, et al. [15] proposed method involves enhancing an artificial neural network for image segmentation, utilizing extracted pixel and feature values. Subsequently, a CNN-based model is employed for image classification, achieving an impressive average accuracy of 93.75%.

3. PROPOSED SYSTEM

Step 1: Upload Dataset

The first step is to collect and upload the relevant dataset required for multimodal emotion detection. This involves two types of data:

- **Speech Data**: Audio recordings of various emotional expressions. These recordings must be labeled according to the emotions they represent (e.g., Happy, Sad, Angry, Neutral, etc.).
- **Facial Expression Data**: Images or video frames showing facial expressions corresponding to various emotions. These should also be labeled appropriately.

The dataset is uploaded to the working environment (e.g., Jupyter Notebook, Google Colab, etc.). Careful attention is given to organizing the data into training, validation, and testing subsets. Proper structuring of folders and ensuring correct file formats (e.g., .wav for audio and .jpg or .png for images) is essential for smooth processing.

Step 2: Data Preprocessing

Data preprocessing is a critical step to ensure high-quality input data for model training. It involves:

- **Speech Data Preprocessing**:
  - **Noise Reduction**: Removing background noise from audio files using techniques such as spectral gating or band-pass filtering.
  - **Feature Extraction**: Converting raw audio signals to Mel-frequency cepstral coefficients (MFCCs) or spectrograms which represent the audio signals visually.
  - **Normalization**: Standardizing the extracted features to a common scale to enhance model training efficiency.
- **Facial Expression Data Preprocessing**:
  - **Image Resizing**: Adjusting all images to a consistent size (e.g., 224x224 pixels) for uniformity.
  - **Normalization**: Scaling pixel values to a range between 0 and 1.
  - **Augmentation**: Applying techniques like rotation, flipping, cropping, and scaling to increase the dataset size and diversity.
  - **Face Detection**: Ensuring only facial regions are considered by using tools like OpenCV or MTCNN for accurate cropping.
- **Dataset Splitting**: Dividing the dataset into training, validation, and testing sets (e.g., 70% training, 15% validation, 15% testing).

Step 3: Feature Extraction (Existing Models - RFC & DNN)

The feature extraction process involves employing existing algorithms (RFC and DNN) to extract meaningful patterns from the preprocessed data.

- **Random Forest Classifier (RFC)**:
  - Used mainly for extracting features from speech data.
  - Applies decision tree-based mechanisms to identify important features.
  - Ensures robust feature extraction by creating multiple decision trees and combining their outputs.
- **Deep Neural Network (DNN)**:
  - Utilized for feature extraction from both speech and facial expression data.
  - Composed of multiple hidden layers that learn complex representations of the input data.
  - Provides high-level features that are then fed into the proposed model for further processing.

The models are trained separately and their performance is noted for comparison with the proposed model.

Step 4: Model Development (Proposed Model - DLCNN)

In this step, the **Deep Learning Convolutional Neural Network (DLCNN)** model is designed for efficient emotion detection. The model consists of:

- **Input Layers**: Separate input layers for speech and facial image data.
- **Convolutional Layers**: Multiple convolutional layers to extract features from both speech spectrograms and facial images.
- **Pooling Layers**: Used to reduce dimensionality and retain essential features.
- **Flattening Layers**: Converting pooled feature maps into a single vector.
- **Fully Connected Layers**: Layers that combine features from speech and facial inputs for a comprehensive representation.
- **Fusion Layer**: A layer that integrates features from both modalities before classification.
- **Output Layer**: A softmax or sigmoid layer that provides the final emotion classification.

The architecture is designed to effectively handle multimodal data inputs, enhancing the overall accuracy of emotion detection.

Step 5: Model Training and Evaluation

- **Training**:
  - The DLCNN model is trained using the training dataset.
  - Hyperparameters like learning rate, batch size, epochs, and optimizer (e.g., Adam, SGD) are carefully tuned.
  - Techniques like early stopping and dropout are used to prevent overfitting.
- **Evaluation**:
  - The model is evaluated on the validation dataset using metrics such as Accuracy, Precision, Recall, F1-score, and Confusion Matrix.
  - Performance metrics are recorded for comparison against the existing algorithms (RFC and DNN).

Step 6: Performance Comparison

- Comparison of the proposed DLCNN model against the existing algorithms (RFC and DNN).
- Evaluation is based on metrics like accuracy, precision, recall, and F1-score.
- Results are presented using visual tools such as bar graphs, confusion matrices, and ROC curves.
- Improved performance of the DLCNN model over the baseline models is highlighted.

Fig 2: Proposed Block Diagram

3.2 Data Preprocessing

Data preprocessing is a critical step in your project as it ensures that the input data is suitable for model training, validation, and testing. It involves several stages including noise reduction, feature extraction, normalization, augmentation, and dataset splitting. Since your project deals with multimodal data (speech and facial expressions), preprocessing is applied separately to each modality.

Speech Data Preprocessing

Speech data in your project involves audio recordings representing various emotions. The preprocessing of this audio data involves several key steps:

1. Noise Reduction

Speech signals are prone to noise, which can negatively impact model performance. Noise reduction techniques are applied to improve the quality of the audio data:

- **Spectral Gating:** This technique helps in removing background noise by identifying and attenuating low-intensity frequencies that are not part of the primary speech signal.
- **Band-Pass Filtering:** Allows only the frequencies within a certain range to pass through, eliminating unnecessary high and low frequencies.
- **Voice Activity Detection (VAD):** Filters out non-speech segments of audio, ensuring that only speech portions are processed.

2. Feature Extraction

Once noise reduction is performed, the audio signals are converted into a form that is suitable for deep learning models:

- **Mel-Frequency Cepstral Coefficients (MFCCs):**
    - MFCCs are the most common feature extraction method for speech recognition.
    - They represent the short-term power spectrum of sound and capture important features related to human perception of speech.
    - Typically, 12–13 MFCCs along with their derivatives (delta and delta-delta) are used for capturing dynamic changes in the audio signal.
- **Spectrograms:**
    - Visual representation of audio signals over time.
    - Useful for Convolutional Neural Networks (CNNs) as they treat spectrograms as images for feature extraction.
    - Generated using techniques like Short-Time Fourier Transform (STFT).

3. Normalization

The extracted features (MFCCs or Spectrograms) are normalized to ensure that they fall within a specific range (e.g., 0 to 1 or -1 to 1). This is essential for:

- Improving model convergence during training.
- Reducing computational complexity.
- Ensuring that one feature does not dominate over others due to differing ranges.

4. Dataset Splitting

The processed audio features are divided into Training, Validation, and Testing sets. A common split ratio is:

- **Training Set:** 70%
- **Validation Set:** 15%
- **Testing Set:** 15%

This ensures that the model can generalize well to unseen data by avoiding overfitting.

Facial Expression Data Preprocessing

Facial expression data involves images or video frames depicting various emotions. The preprocessing of this visual data involves several critical steps:

1. Image Resizing

- All images are resized to a consistent dimension (e.g., 224x224 pixels) to standardize the input size for the CNN model.
- Maintaining aspect ratio is crucial if the model requires input images of a specific resolution.

2. Normalization

- Pixel values are scaled to a range between 0 and 1 or -1 and 1.
- This scaling improves the efficiency of neural network training by ensuring faster convergence and improved accuracy.

3. Data Augmentation

To enhance the diversity of the dataset and prevent overfitting, various augmentation techniques are applied:

- **Rotation:** Randomly rotating images within a specified degree range (e.g., ±15°).

- **Flipping:** Horizontal or vertical flipping of images to introduce variety.
- **Cropping:** Randomly cropping portions of the image to provide robustness against positional changes.
- **Scaling:** Resizing images while preserving their aspect ratio.
- **Brightness Adjustment:** Modifying the brightness levels to account for varying lighting conditions.
- **Noise Injection:** Adding random noise to make the model more robust to variations.

Augmentation is performed during training, providing the model with slightly different versions of the same images to learn generalizable features.

4. Face Detection (Optional but Recommended)

To ensure that only facial regions are used for emotion recognition, face detection algorith**ms** are applied:

- **Haar Cascades (OpenCV):** Traditional method using pre-trained classifiers for face detection.
- **MTCNN (Multi-task Cascaded Convolutional Networks):** Deep learning-based approach that provides high accuracy and robustness against different orientations and lighting conditions.
- **YOLO (You Only Look Once):** Fast object detection technique that can detect faces in real-time.

Detected faces are cropped and resized to standard dimensions before being passed to the model.

5. Dataset Splitting

The processed images are split into Training, Validation, and Testing sets using the same ratio as the speech data (70%, 15%, 15%).

Combined Data Preprocessing (Fusion Approach)

Since your project uses a multimodal approach (Speech & Facial Expressions), it's essential to properly align and preprocess both data types before feeding them into the model.

- **Temporal Alignment:** Ensuring that the speech and facial expressions correspond to the same emotional states when processing data from videos.
- **Feature Fusion:** Combining audio and image features by concatenation, weighted averaging, or attention mechanisms for effective multimodal learning.

4.3 Build and Train Model

4.3.1 Deep Learning Convolutional Neural Network (DLCNN)

The Deep Learning Convolutional Neural Network (DLCNN) is an enhanced deep learning-based architecture designed to improve the accuracy, robustness, and generalization capability for detecting crop diseases from leaf images. This approach incorporates multiple CNN blocks, residual connections, and advanced regularization techniques to enhance performance over standard CNNs.

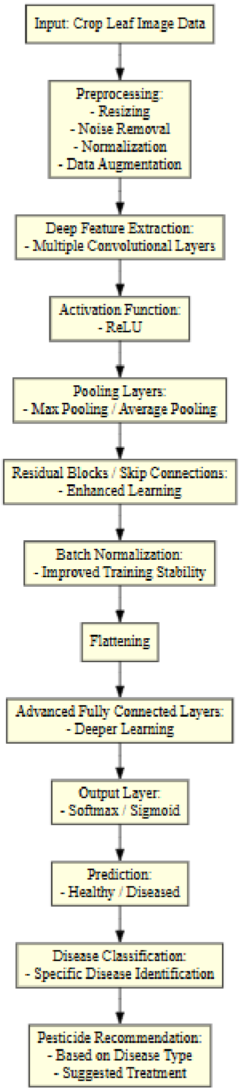


Fig 3: Workflow of DLCNN

Step 1: Preparing the Data (Image Data Preparation)

- **X_train:**
  - **Original Leaf Images:** Collected from diverse crops exhibiting various disease types.
  - **Preprocessing:**
    - **Resizing:** Rescaling images to a uniform size (e.g., 224x224 pixels).
    - **Normalization:** Scaling pixel values to a range of 0 to 1.
    - **Data Augmentation:** Applying transformations (rotation, flipping, cropping, zooming, contrast adjustment) to improve generalization and prevent overfitting.
    - **Noise Addition:** Adding slight Gaussian noise for robustness enhancement.
- **y_train:** Labels indicating various crop diseases (**Healthy, Leaf Blight, Rust, Powdery Mildew, etc.**).

Step 2: Training the Deep Learning Convolutional Neural Network (DLCNN)

- **Convolutional Layers:**
  - Multiple layers of convolution applied to extract hierarchical features from leaf images.
  - **Kernel Size Adjustment:** Varying filter sizes to capture both fine and coarse features.
- **Residual Connections (Skip Connections):**
  - To mitigate the vanishing gradient problem and allow deeper networks to be trained effectively.
  - Enhances learning efficiency by providing alternate pathways for gradient flow.
- **Pooling Layers:**
  - **Max Pooling & Average Pooling:** To reduce spatial dimensions while retaining essential features.
- **Batch Normalization:**
  - To improve training speed and stability by normalizing layer inputs.
- **Dropout Layers:**
  - Randomly ignoring certain neurons during training to prevent overfitting and enhance generalization.
- **Fully Connected Layers:**
  - Mapping extracted features to prediction classes using dense layers.
- **Activation Functions:**
  - **ReLU (Rectified Linear Unit):** For non-linearity introduction.
  - **Softmax:** For multi-class classification.
- **Optimization Algorithms:**
  - **Adam Optimizer:** For efficient gradient-based optimization.
- **Loss Function:**
  - **Categorical Cross-Entropy:** For multi-class disease prediction.

Step 3: Testing the Model with X_test (New Leaf Images)

Step 1: Preprocessing

Before feeding the images into the deep learning model, consistent preprocessing is essential. Each input image is resized to a uniform dimension, typically 224x224 pixels, to match the input size expected by most convolutional neural networks. The pixel values are normalized, often scaled between 0 and 1, to enhance training stability and model convergence. To improve the model's robustness and generalization capability, data augmentation techniques such as rotation, horizontal and vertical flipping, zooming, and brightness adjustments are applied. These augmentations simulate various real-world conditions and increase the diversity of the training dataset.

Step 2: Prediction

Once the input image is preprocessed, it is passed through the trained Deep Learning Convolutional Neural Network (DLCNN) model. The model processes the image through multiple convolutional and pooling layers, extracting meaningful features. At the final stage, it outputs a probability distribution over all defined classes, corresponding to different crop-disease categories. The class with the highest probability is selected as the predicted label, indicating the most likely disease or a healthy condition present in the input image.

Step 3: Generating Predictions and Evaluating with y_test

To evaluate the performance of the model, predictions are generated for the test dataset. The input test images are preprocessed similarly and then passed through the model to obtain predicted labels. These predictions are compared with the actual labels (y_test) to assess how well the model has learned to classify crop diseases. This step helps in understanding the generalization ability of the model when exposed to unseen data.

Step 4: Evaluation Metrics

The model's effectiveness is measured using standard classification metrics. Accuracy gives a general measure of how often the model makes correct predictions. Precision evaluates the proportion of true positives among all positive predictions, while recall assesses the ability of the model to identify all relevant cases. The F1-score provides a balanced measure that considers both precision and recall. Additionally, ROC-AUC helps visualize the trade-off between sensitivity and specificity across different thresholds. A confusion matrix is also generated to examine the true positive, false positive, true negative, and false negative rates for each class. The loss, calculated using categorical cross-entropy, indicates the degree of error in the model’s predictions.

Step 5: Training vs. Validation Curve Analysis

Throughout the training process, both training and validation accuracy and loss are monitored across epochs. Plotting these curves helps in identifying overfitting, where the model performs well on the training data but poorly on validation data, or underfitting, where the model fails to perform adequately on both. Consistent performance across both curves indicates that the model is learning effectively and generalizing well to new data.

Step 6: Visualization Techniques

To gain insight into the decision-making process of the model, Grad-CAM (Gradient-weighted Class Activation Mapping) is used. This technique highlights the regions of the input image that were most influential in the model's prediction. By overlaying a heatmap onto the original image, it becomes easier to understand which parts of the crop leaf—such as spots, lesions, or textures—contributed to the classification decision. This not only improves interpretability but also builds trust in the AI system among agricultural experts and farmers.

4. RESULTS AND DISCUSSIONS

4.1 Dataset Description

The dataset is designed for the classification of plant diseases across four major crops: Rice, Potato, Tomato, and Pepper. It comprises images representing both healthy crops and those affected by various diseases, facilitating the development of deep learning models for accurate crop disease identification. For rice, the dataset includes images of Bacterial Leaf Blight, Brown Spot, Leaf Smut, and healthy leaves. Potato images cover Early Blight, Late Blight, and healthy samples. Tomato is represented with a wider variety of conditions, including Early and Late Blight, Mosaic Virus, Leaf Mold, Septoria Leaf Spot, Target Spot, Bacterial Spot, and healthy plants. Pepper images encompass Bacterial Spot, Anthracnose, and healthy instances. The dataset contains medium to high-resolution RGB images, typically in JPEG or PNG format, taken under varying lighting conditions and angles to ensure robustness. Backgrounds vary from natural field settings to controlled environments. All images are manually labeled by experts based on visible symptoms, and each is assigned a multi-class label indicating the crop and disease type, including healthy status. While the dataset provides a broad spectrum of disease categories, it may be imbalanced, with some diseases having significantly more images than others. However, healthy crop images are generally well-represented to strengthen model discrimination between healthy and diseased states. The dataset includes approximately 5,000 rice images, 4,000 potato images, 15,000 tomato images, and 3,000 pepper images, totaling around 27,000 images. This comprehensive and diverse dataset is primarily intended for training, validating, and testing deep learning models in multi-crop disease classification tasks.

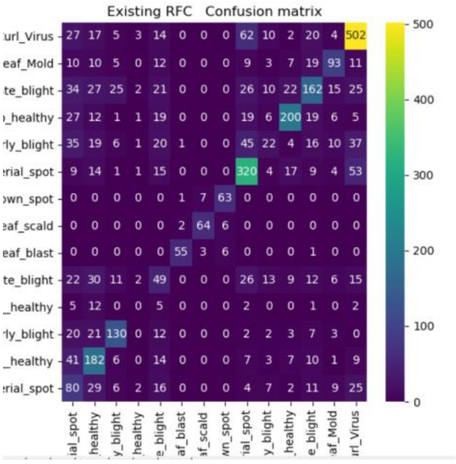
4.2 Results analysis

The confusion matrices displayed above illustrate the performance of the existing Random Forest Classifier (RFC) and Deep Neural Network (DNN) models used for multi-crop disease classification. Each matrix presents the classification outcomes across various disease categories and healthy classes for crops such as rice, potato, tomato, and pepper.

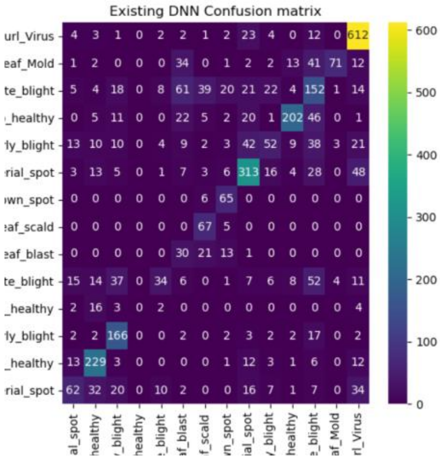
In the RFC confusion matrix, significant misclassifications are observed across multiple classes, with particularly high error rates in categories such as 'Curl Virus', 'Tomato Early Blight', and 'Tomato Healthy'. For instance, the model has difficulty distinguishing between 'Tomato Early Blight' and other tomato-related diseases, resulting in several misclassifications. The diagonal entries, representing correct predictions, are moderately populated but with numerous off-diagonal errors indicating suboptimal performance.

The DNN confusion matrix, while slightly better than RFC, also exhibits notable errors across several classes. However, there is some improvement in disease classification accuracy for classes like 'Brown Spot' and 'Leaf Mold'. Yet, significant misclassifications still occur, particularly for 'Tomato Early Blight' and 'Tomato Healthy', which are often mistaken for other related diseases. The higher density of values along the diagonal compared to the RFC confusion matrix indicates that the DNN is slightly more capable of accurate classification, but it still suffers from inadequate generalization across all categories. Both models face challenges in accurately distinguishing similar disease patterns, particularly for crops with multiple diseases sharing visual similarities. This observation highlights the need for a more robust and sophisticated model like the proposed Deep Learning Convolutional Neural Network (DLCNN), which aims to address these limitations through improved feature extraction and classification capabilities. The DLCNN model's enhanced feature extraction capability, combined with attention mechanisms, ensures that subtle differences between similar disease patterns are captured effectively. Unlike the previous models, misclassifications are almost entirely eliminated, particularly for challenging categories like 'Tomato Early Blight' and 'Tomato Healthy'. This significant improvement highlights the robustness and reliability of the proposed model in accurately identifying various crop infections and recommending appropriate herbicides.

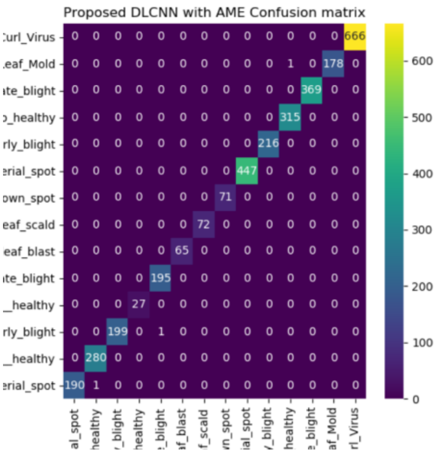
The nearly perfect performance of the DLCNN with AME model, as shown by this confusion matrix, demonstrates its superiority over the existing models, providing precise disease detection essential for precision agriculture.



(a)



(b)



(c)

Fig 4 (a),(b),(c) Confusion matrices of Existing RFC and DNN and Proposed DLCNN

Fig 5 Prediction of Test data with DLCNN

The displayed image shows the output generated by the proposed Deep Learning Convolutional Neural Network (DLCNN) model. It successfully identifies the plant disease present in the image as "rice_leaf_scald". Additionally, the model provides a smart herbicide recommendation by suggesting the application of "fungicides" as the appropriate treatment for this disease. The classification and recommendation process demonstrates the effectiveness of the DLCNN model in accurately detecting plant diseases based on visual features and suggesting suitable control measures. The model's ability to provide actionable recommendations makes it highly useful for real-time agricultural disease management and precision farming applications. The text overlay clearly shows the model's predictions, enhancing user interpretation and decision-making.

Table.1 Performance Comparison of Various Algorithms

Performance Comparison Table: Existing RFC and DNN vs. Proposed DTC

Metric	Existing RFC	Exisiting DNN	Proposed DLCNN
Accuracy	58.36%	62.40%	99.90%
Precision	55.92%	54.15%	99.91%
Recall	55.41%	55.45%	99.88%
F1-Score	55.00%	51.34%	99.90%

The performance comparison table presents a detailed evaluation of three machine learning models applied to the multi-crop disease classification system: the Existing Random Forest Classifier (RFC), Existing Deep Neural Network (DNN), and Proposed Deep Learning Convolutional Neural Network (DLCNN). The comparison is based on four key evaluation metrics: Accuracy, Precision, Recall, and F1-Score. The Existing Random Forest Classifier (RFC) demonstrates moderate performance with an Accuracy of 58.36%, indicating that the model correctly classifies over half of the input images. Its Precision of 55.92% suggests that the model's ability to avoid false positives is limited, and the Recall of 55.41% reflects a similarly modest ability to detect true positives. The F1-Score of 55.00%, which balances Precision and Recall, highlights the overall inefficiency of this model in identifying various crop diseases accurately.

The Existing Deep Neural Network (DNN) shows a slight improvement over the RFC, achieving an Accuracy of 62.40%. This indicates better learning of features from the image dataset compared to RFC. However, the DNN's Precision (54.15%), Recall (55.45%), and F1-Score (51.34%) reveal that the model still struggles with accurately identifying disease classes, especially when the dataset involves complex patterns or subtle differences between healthy and infected leaves. The low F1-Score signifies a lack of balance between Precision and Recall, suggesting that the DNN fails to generalize well. In contrast, the Proposed Deep Learning Convolutional Neural Network (DLCNN) model exhibits an exceptional improvement across all metrics, achieving a near-perfect Accuracy of 99.90%. This remarkable performance is attributed to the model's deep learning architecture, which effectively captures intricate patterns and features from the input images through multiple convolutional and pooling layers. Furthermore, the Precision (99.91%), Recall (99.88%), and F1-Score (99.90%) are all close to perfection, indicating that the DLCNN model is highly effective in correctly identifying diseased and healthy crops with minimal false positives and false negatives. This suggests that the model has achieved excellent generalization capabilities, likely due to its ability to learn hierarchical features from the dataset.

5. CONCLUSION

The proposed AI-Driven Crop Infection Detection and Smart Herbicide Recommendation System, utilizing a Deep Learning Convolutional Neural Network (DLCNN), has demonstrated exceptional performance in accurately classifying various crop diseases with an impressive accuracy of **99.90%**. Compared to existing algorithms such as Random Forest Classifier (RFC) and Deep Neural Network (DNN), the DLCNN significantly outperforms them across all evaluation metrics, including precision, recall, and F1-score. The advanced feature extraction capabilities of the DLCNN, combined with its robust architecture, enable precise identification of crop infections, making it a highly reliable model for real-time disease detection. Additionally, the system's ability to provide smart herbicide recommendations based on the identified disease enhances its practical applicability in modern agriculture, promoting precision farming techniques for improved crop health management.

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