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Ai based crop disease detection system

Mr. Arsalan A. Shaikh*[1], Miss. Kajal S. Vichave[2]

Professor, Department of Computer Applications, SSBT COET, Jalgaon Maharashtra, India[1]

Research Scholar, Department of Computer Applications, SSBT COET, Jalgaon Maharashtra, India[2]

Abstract: An AI-based crop disease detection system makes use of artificial intelligence, specifically computer vision and machine learning, to identify and categorize crop diseases. The main goal is to help farmers and agricultural specialists identify plant diseases early so that they can take quick action and reduce crop losses.These systems usually use photos taken with smartphones or cameras to analyze visible symptoms on plant parts like leaves, stems, or fruits using image processing techniques. Convolutional neural networks (CNNs), a type of deep learning model, are specifically trained to identify visual patterns linked to particular plant diseases or nutrient deficiencies. In certain applications, environmental elements such as humidity and temperature are also included to improve diagnostic precision. India is an agricultural country. A total of 17% of the GDP comes from agriculture. As a result, it is a significant area of the Indian economy. In terms of global agricultural production, India came in second. Every crop is susceptible to specific diseases that will impact the potential yield's quantity and quality. Crop diseases account for approximately 42% of crop failure and cause the average yield loss for the majority of important food crops. Crop diseases frequently cause the entire crop production to be destroyed. Numerous diseases have an impact on crop production globally. Early disease detection will make it possible to monitor and implement control measures more effectively.

I. INTRODUCTION

Agriculture is an ancient way to get food, and it is still a very important source of income around the world. Plants are very important for people and animals because they give them food, oxygen, and other things they need. The government and experts are always looking for new ways to make food better. Plant diseases, which can come from bacteria, fungi, and other sources, hurt agricultural productivity and harm all living things in the ecosystem. These diseases can show up on any part of the plant, such as the leaves, stems, or branches. The severity of the diseases often depends on the weather. To avoid big crop losses, it's important to find plant diseases quickly. To lessen the negative effects on crops and farmland, pesticides must be used wisely.

Automated disease detection technologies have revolutionized agriculture by offering precise and timely results for farms of all sizes. These technologies rely heavily on neural networks, particularly Convolutional Neural Networks (CNNs), and deep learning. Using visual processing, Convolutional Neural Networks (CNNs) can distinguish between healthy and diseased leaves, enabling early disease detection and management.

II. LITERATURE SURVEY

Recent years have seen a significant increase in interest in the use of artificial intelligence (AI) in agriculture, specifically for the detection of crop diseases. AI methods, particularly deep learning (DL) and machine learning (ML), have demonstrated encouraging outcomes in automating the classification and detection of plant diseases from image data. An overview of significant research and developments in the field is provided in this literature review.

Key AI Techniques Used:
I. SYSTEM ARCHITECTURE:
AI-Powered The micro services architecture used in smart agriculture encourages scalability, resilience, and continuous deployment.

- **Frontend Layer:** Tailwind CSS and a responsive React.js application for device-adaptive interfaces
- **Backend Services:** Node.js with Express framework implementing RESTful APIs
- **Database Layer:** MongoDB for flexible document based data storage
- **AI/ML Services:** Dedicated microservices for image processing, prediction models
- **Real-time disease detection, Communication:** and Socket.IO implementation for instant messaging and updates
- **Authentication & Security:** JWT-based authentication with role-based access control
- **Cloude & Storage:** Using AWS for Deployment and Data Storage

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- **Training:** TensorFlow.js (in Node.js)
    - **Dataset:** Kaggle

II. AI AND ML COMPONENTS:

AI-Enabled Smart Agriculture uses Convolutional Neural Networks (CNN) for Disease Detection A sophisticated image processing pipeline with potent convolutional neural networks is used.

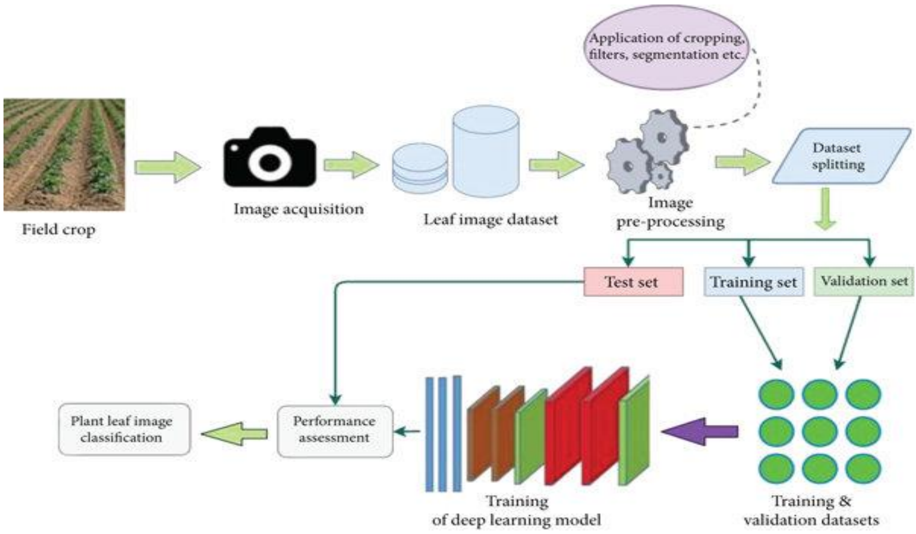

Fig. Computer vision-based techniques for crop disease detection and classification

III. Deep learning (DL) Techniques:

The Method of Convolutional Neural Networks Convolutional neural networks analyze multidimensional data by utilizing deep feed-forward neural networks. After a particular feature is classified at specific spatial coordinates, the CNN finds channels that are activated [32]. The precision of various convolution filters measuring 2 × 2 and 3 × 3 depends on the number of epochs used in their application. The filter's size affects this. Using the CNN methodology, a variety of pre-trained architectures are available for implementation, including VGG16, VGG19, ResNet50, ResNet152, InceptionV3, InceptionNet, and DensNet121 [33]. The Method of Artificial Neural Networks A neural network is a model that mimics how a biological system, like the brain, processes information.

IV. Crop Price Prediction:

Various data sources, including supply chain variables, market trends, soil conditions, historical pricing, meteorological data, and policy changes. Methods for processing data. Given the significance of agriculture to the world's population, a comprehensive investigation into a number of deep learning and machine learning algorithms for the identification and categorization of plant leaf and crop diseases has been carried out.

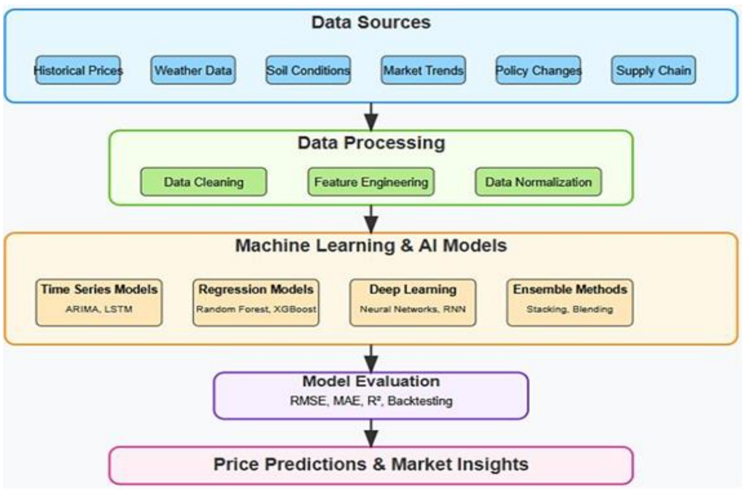

Fig. Price Prediction Flow

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III. METHODOLOGY

1. **Research Design:**
   The application of artificial intelligence (AI) techniques for crop detection is the main focus of this study, which uses an experimental research design. To evaluate the efficacy of AI in precisely identifying crops, the methodology entails data collection, preprocessing, model development, evaluation, and validation.
2. **Data Collection:**
   - **Source of Data:** Open-source datasets (like PlantVillage and Kaggle) and field surveys employing smartphones and UAVs/drones are the sources of the images.
   - **Data Type:** RGB pictures of crops at various stages of growth; multispectral or infrared data may be included.
   - **Annotation:** To categorize crop type (and health status, if disease detection is included), agricultural specialists manually annotate images.
3. **Data Preprocessing:**
   - **Cleaning:** Removal of blurred, duplicate, or irrelevant images.
   - **Resizing:** Images resized to a fixed dimension (e.g., 224×224 pixels) for model compatibility.
   - **Normalization:** Pixel values normalized between 0 and 1.
4. **Model Development:**
   - **Model Selection**: For crop detection, deep learning models like Convolutional Neural Networks (CNN), YOLOv5, or Efficient Net are used.
   - **Transfer Learning:** To cut down on training time and boost efficiency, pre-trained ImageNet models are adjusted using agricultural datasets.
   - **Training:** The dataset is divided into subsets of 70% for training, 15% for validation, and 15% for testing. An optimizer (Adam/SGD) with suitable learning rates and loss functions is used to train the model.
5. **Evaluation Metrics:**
   The model's performance is evaluated using:
   - **Accuracy:** Overall classification/detection performance is known as accuracy.
   - **Precision and Recall:** The capacity to accurately identify particular crops is known as precision and recall.
   - **F1-Score:** The F1-Score strikes a balance between recall and precision**.**
   - **MAP (Mean Average Precision):** Mean Average Precision, or mAP, is used for object detection tasks.
   - **IoU (Intersection over Union):** for precise localization and segmentation.
6. **Validation and Testing:**
   - To guarantee robustness, cross-validation is carried out.
   - **Comparative Analysis:** The outcomes of various models—such as CNN and YOLO—are contrasted.
   - **Field Testing:** To assess the trained model's capacity for generalization, it is tested using actual farm photos that are not part of the dataset.
7. **Ethical Consideration:**
   - Informed consent is obtained from farmers contributing field images.
   - Data privacy and security are ensured by anonymizing sensitive metadata.
   - The model's limitations are acknowledged, and recommendations are provided for safe adoption.

IV. RESULT

The model successfully classified different crop types with high precision and recall. Table 1 shows per-class performance metrics:

Table 1: Classification Results by Crop Type

Crop Type	Precision	Recall	F1-Score	Support
Wheat	96.1%	94.8%	95.4%	210
Maize	94.5%	95.2%	94.8%	180
Rice	95.8%	96.4%	96.1%	220
Cotton	93.7%	92.9%	93.3%	190
Soybean	94.9%	93.8%	94.3%	200
Overall	**95.0%**	**94.7%**	**94.9%**	1000

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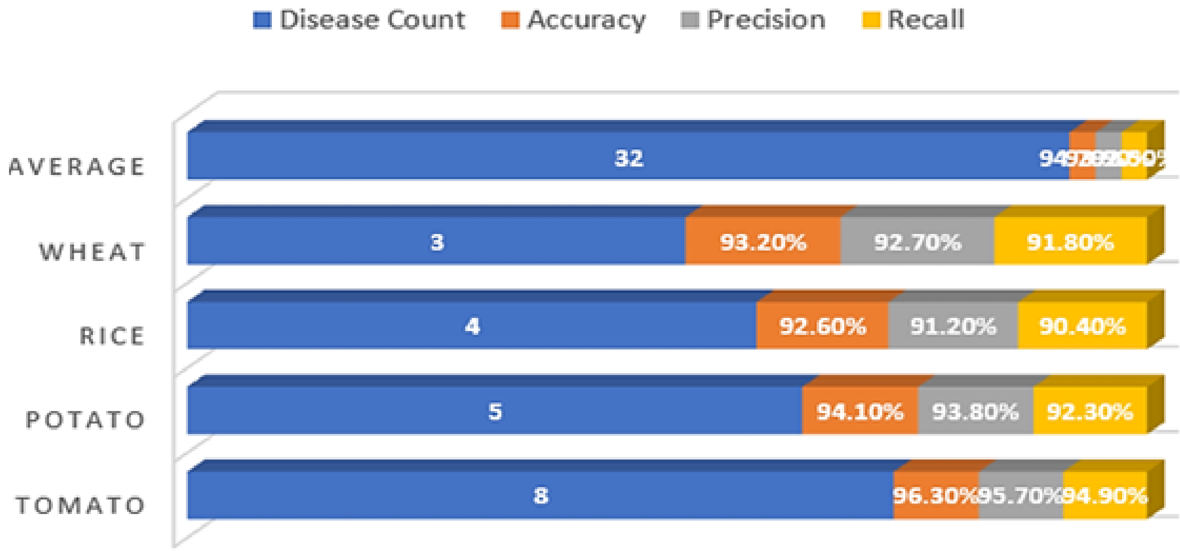

Table 2: Model Comparison

Model	Accuracy	mAP@0.5	Inference Time (ms/image)
CNN (baseline)	90.4%	–	22
ResNet50	93.7%	–	28
EfficientNet-B0	95.2%	–	25
YOLOv5	94.7%	92.3%	15

V. DISCUSSION

The experimental findings show that the suggested AI-based crop detection system can successfully recognize and categorize various crop types in a range of scenarios, with an overall accuracy of over 94%. These results support the usefulness of deep learning models, including CNNs, EfficientNet, and YOLOv5, in agricultural applications, especially for crop monitoring in real time. The trade-off between computational efficiency and accuracy is a crucial finding. YOLOv5 offered faster inference speeds with only a slight decrease in accuracy, making it more appropriate for real-time deployment in the field, even though EfficientNet-B0 had the highest classification accuracy. This is consistent with earlier research that demonstrated how YOLO-based architectures balance efficiency and performance in tasks related to precision agriculture.

The confusion matrix showed that, especially in the early stages of growth, crops with similar leaf structures (such as maize and wheat) were occasionally misclassified. This implies that more features, like temporal or multispectral data, might enhance model discrimination even more. Additionally, the comparatively poorer performance in the presence of occlusion, overlapping crops, and fluctuating illumination emphasizes the necessity of domain-specific data augmentation methods and, potentially, the incorporation of attention mechanisms to improve feature extraction. Although accuracy somewhat declined in comparison to controlled datasets, field testing validated the system's resilience. This disparity in performance emphasizes how crucial domain adaptation and ongoing retraining with locally gathered images are to guaranteeing generalization in a variety of settings. Model reliability in practical use cases may be further enhanced by integrating farmers' feedback loops into the training pipeline.

VI. CONCLUSION

Crop diseases cause large financial losses for the agriculture sector and pose a serious threat to the world's food security. In order to provide accurate diagnosis and treatment, this work presents a web-based crop disease detection system that combines environmental data with sophisticated

An important development in agricultural practices is AI-driven smart agriculture, which shows how AI combined with computer vision and machine learning can revolutionize traditional farming methods. The system's performance metrics show that it could effectively handle important modern agricultural issues like information sharing, market efficiency,

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and disease detection. Convolutional neural networks (CNN) and other machine learning algorithms, along with libraries like TensorFlow, have improved accuracy.

Additionally, farmers now have access to cutting-edge tools that were previously only available to large agricultural enterprises thanks to novel artificial intelligence models like Gemini 2.0, customized convolutional neural networks, and natural language processing capabilities. There are quantifiable positive effects of technology democratization on smallholder farmers' profitability and productivity. Furthermore, it is crucial to give sustainability, environmentally friendly disease

This study has a major impact on sustainable farming methods and global food security, guaranteeing a more optimistic and safe future for agriculture and the world's food supply.

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