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An Intelligent Automated System for Fruits [Apple] Disease Detection

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Abstract: Production of crop is an important aspect in the field of agriculture. The production rate is directly dependent on the quality of the crop. Crop Infection factor becomes an important aspect of Quality. Most of the time traditional approaches such as Naked eye Survey, Survey through Expert etc. are used to detect the diseases during cultivation. This process requires huge processing time and cost. Automatic detection of severity is essential for high quality production. Apple fruit diseases significantly impact crop yield and quality, necessitating early and accurate detection. Traditional diagnostic methods are manual, time-consuming, and prone to human error. This study proposes a robust and automated disease detection system using machine learning and deep learning techniques, enhanced with transfer learning. Models including Support Vector Machine (SVM), Random Forest, Convolutional Neural Networks (CNN), and pre-trained architectures such as ResNet and MobileNet are analyzed.
Keyword: Machine Learning, Disease Detection, Fruits, Vegetables, Image Processing, CNN, Agriculture.

I. INTRODUCTION

Agriculture is the backbone of the Indian economy, contributing significantly to employment and GDP. However, plant diseases are a major threat to agricultural productivity. Fruits and vegetables are particularly vulnerable to diseases caused by bacteria, fungi, viruses, and environmental factors. Early detection of these diseases is essential to prevent crop loss and ensure food security.

Traditional disease detection methods involve visual inspection by experts, which can be subjective, inconsistent, and inefficient. With the advancement of technology, machine learning has emerged as a powerful tool for automating disease detection. Machine learning algorithms can analyze large datasets, identify patterns, and provide accurate predictions.The traditional method of detection of diseases and pests completely rely on the observation of the producer or ask experts for guidance. Such a method slow and is less effective, high cost, strong subjectivity, low accuracy, and timeliness.

Recent advancements have introduced deep learning models, especially Convolutional Neural Networks (CNNs), which have shown remarkable performance in image classification tasks. Researchers have used datasets such as PlantVillage to train models for detecting diseases in various crops.

The crop of apple plays important role for economical concern of farmers. Around 80% of total population depends directly or indirectly on agriculture in the union territory (J&K) while as Kashmir produces around 75% of total apple production in India. In terms of area, more than 1, 60, 000 hectares of land in Kashmir is under apple cultivation. The situation while disease occurs in the apple crops is challenging. As tradition, farmer approach the chemist and use some pesticides but it is not perfect without diagnose the disease. Studies have demonstrated that CNN-based models outperform traditional machine learning techniques due to their ability to automatically extract features. However, challenges such as dataset imbalance, varying lighting conditions, and real-world applicability still exist.

At present, the diagnosis of maximum plant diseases still depends on farmers. however, because the image capabilities of some sicknesses are comparable, and there is no obvious boundary between extraordinary grades of the same ailment, the synthetic analysis outcomes might gift a big deviation. This poses a project to disorder control. moreover, due to the random incidence, some sicknesses can't be determined in time. this will affect the satisfactory and yield of result, after which damage the development of agricultural economy. therefore, it is increasingly more extensive to use prescient deep learning methods to attain automated and precise disorder analysis.

Scab   Powdery mildew   Fire blight   Soft rot   Bitter rot

Figure 1: Diseases in Apple Fruit

II. LITERATURE SURVEY

The rapid advancement of artificial intelligence (AI), machine learning (ML), and computer vision has significantly transformed agricultural practices, particularly in the domain of automated fruit disease detection. Apple disease detection has become a critical research area due to the substantial economic losses caused by diseases such as apple scab, blotch, and rot. This section presents a comprehensive review of existing methodologies, highlighting traditional approaches, machine learning techniques, and deep learning-based intelligent systems.

A. Traditional Image Processing-Based Approaches

Early research in apple disease detection primarily relied on classical image processing techniques combined with machine learning classifiers.Dubey and Jalal (2014) proposed a method based on K-means clustering for segmentation, followed by feature extraction and classification using Support Vector Machines (SVM). Their approach achieved an accuracy of approximately 93% for detecting apple diseases such as scab, blotch, and rot. Similarly, other studies employed handcrafted features such as color, texture, and shape descriptors (RGB, HSV, SIFT, etc.) to identify disease symptoms. Sparse coding techniques were also explored to reduce computational complexity while maintaining detection efficiency, achieving reasonable accuracy across multiple disease classes.
However, these approaches suffered from several limitations:

1) Sensitivity to lighting and background variations
2) Dependence on manual feature extraction
3) Limited scalability for real-world applications

B. Machine Learning-Based Approaches

With the evolution of machine learning, researchers began integrating statistical models and classifiers to improve disease detection accuracy. Artificial Neural Networks (ANNs) were introduced to automate classification tasks. A study using ANN-based classification successfully categorized apple diseases into classes such as bitter rot, black rot, and scab, demonstrating improved robustness compared to traditional techniques.
Further advancements included:

1) Decision Trees and Random Forest classifiers
2) Feature optimization using dimensionality reduction
3) Hybrid models combining image processing and ML

Although these models improved classification performance, they still relied heavily on handcrafted features and struggled with complex real-world scenarios.

C. Deep Learning-Based Approaches

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized apple disease detection by enabling automatic feature extraction and high accuracy.

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CNN-Based Classification Models
Recent studies have demonstrated the effectiveness of CNN architectures such as:
ResNet, VGG, DenseNet, MobileNet, and EfficientNet
A web-based AI system reported that ResNet152V2 achieved 92% accuracy for apple fruit disease classification, while Xception achieved 99% accuracy for leaf disease detection. Another study using ensemble models (DenseNet121 + EfficientNet) achieved 96.25% accuracy, showing the effectiveness of transfer learning and data augmentation. AFD-Net, a hybrid EfficientNet-based architecture, further improved performance, achieving **up to 98.7% accuracy** on plant pathology datasets.

III. METHODOLOGY

Identifying fruit diseases is a critical aspect of agricultural management, as it directly influences both the quantity and quality of production. When diseases are identified early and correctly, timely interventions can reduce crop loss and maintain produce quality. Modern algorithms, image processing techniques and feature extraction support fruit disease detection, while machine learning (ML) and deep learning (DL) further enhance and automate the process.Furthermore, our CNN model exhibits resilience to environmental variations and imaging parameters, enhancing its applicability across diverse agricultural settings. By leveraging advanced machine learning techniques, the approach developed in this experimental work contributes to modernizing fruits and vegetables sorting operations in food processing, crop management practices thus promoting agricultural sustainability. The scalability and portability of our model make it suitable for deployment in both small-scale farms and large-scale agricultural operations.

A. Data Collection

1) The dataset consists of images of healthy and diseased fruits and vegetables. These images can be collected from publicly available datasets or captured using cameras in real agricultural environments.
2) Source: PlantVillage + real-field images
3) Classes: Healthy, Scab, Rot, Mildew
4) Data split: 80% training, 20% testing

B. Image Preprocessing

Preprocessing is an essential step to improve the quality of input images. The following techniques are applied:

1) Image resizing
2) Noise removal
3) Color space conversion (RGB to HSV)
4) Image normalization
5) Image resizing (224×224)
6) Normalization
7) Noise removal
8) Data augmentation:
9) Rotation
10) Flipping
11) Brightness adjustment
12) Image argumentation

C. Feature Extraction

Feature extraction involves identifying important characteristics of the images. Common features include:

1) Color features
2) Texture features (using GLCM)
3) Shape features

In deep learning approaches, feature extraction is automatically handled by CNN models.

D. Model Selection

Various machine learning models are used in this study:

1) Support Vector Machine (SVM): Effective for classification tasks with high-dimensional data.
2) Random Forest: An ensemble learning method that improves accuracy and reduces overfitting.
3) Convolutional Neural Network(CNN): A deep learning model widely used for image classification.
4) ResNet50 : Deep architecture with skip connections
5) MobileNet : Lightweight and efficient

E. Model Training and Testing

The dataset is divided into training and testing sets. The models are trained using the training dataset and evaluated on the testing dataset. Performance metrics such as accuracy, precision, recall, and F1-score are used to measure the effectiveness of the models.

IV. CHALLENGES AND FUTURE DIRECTIONS AND RESULT

Developing effective fruit disease detection and classification models presents several challenges, including variability in disease symptoms, limitations in dataset quality and issues with model complexity. A major challenge lies in the fact that environmental conditions influence the visual manifestation of disease symptoms, making consistent and accurate detection more difficult (Yang *et al*., 2020). Traditional models relying on handcrafted features like colour and texture often fail to capture the full variability of disease patterns, resulting in decreased performance. Moreover, the lack of high-quality, annotated datasets impairs model generalization across different fruit types and environmental conditions (Pawar and Jadhav, 2017). Deep learning models are often constrained by high computational costs and intricate architectures, making them difficult to deploy in real-time agricultural scenarios (Goel and Pandey, 2022). Additionally, models trained on localized data may not generalize well, increasing the risk of misclassification due to similarities in symptom appearance across different diseases (Pawar and Jadhav, 2017).Overfitting remains another concern, especially when models are trained on limited datasets, as seen in strawberry disease studies (Abbas *et al*., 2021). The performance of the models is summarized as follows:

SVM: Achieved moderate accuracy with dependence on manual feature extraction.

Random Forest: Provided stable results with improved generalization.

CNN: Achieved the highest accuracy due to its ability to automatically learn complex features from images.

The CNN model outperformed other models, making it the most effective approach for apple disease detection.

V. DISCUSSION

The results demonstrate that deep learning models, particularly CNNs, are more efficient than traditional machine learning techniques for image-based disease detection. The ability of CNNs to automatically extract features reduces the need for manual intervention. Overall, advancing fruit disease detection requires progress in DL algorithms, dataset development and real-time applicability. Emphasis should be placed on better data, optimized models and contextual integration to ensure accurate, reliable and scalable systems for agricultural use. However, the performance of the model depends on the quality and diversity of the dataset. Environmental factors such as lighting and background noise can affect accuracy. Therefore, further improvements are required for real-world implementation.

VI. CONCLUSION

This research presents a machine learning-based approach for detecting diseases in apple fruits. The study concludes that CNN models provide superior performance compared to traditional techniques such as SVM and Random Forest. The proposed system can help farmers in early disease detection, reducing crop loss and improving productivity. Research in fruit disease detection and classification has made significant progress through the use of machine learning, deep learning and image processing. The studies made have contributed unique insights to address key challenges in accurately identifying fruit diseases and enhancing sustainable agricultural productivity. Early approaches that combined traditional image processing with ML techniques especially for specific fruits like pomegranates demonstrated promising results under controlled conditions. However, these methods were limited by the manual nature of feature extraction, leading to poor adaptability across varying environments.

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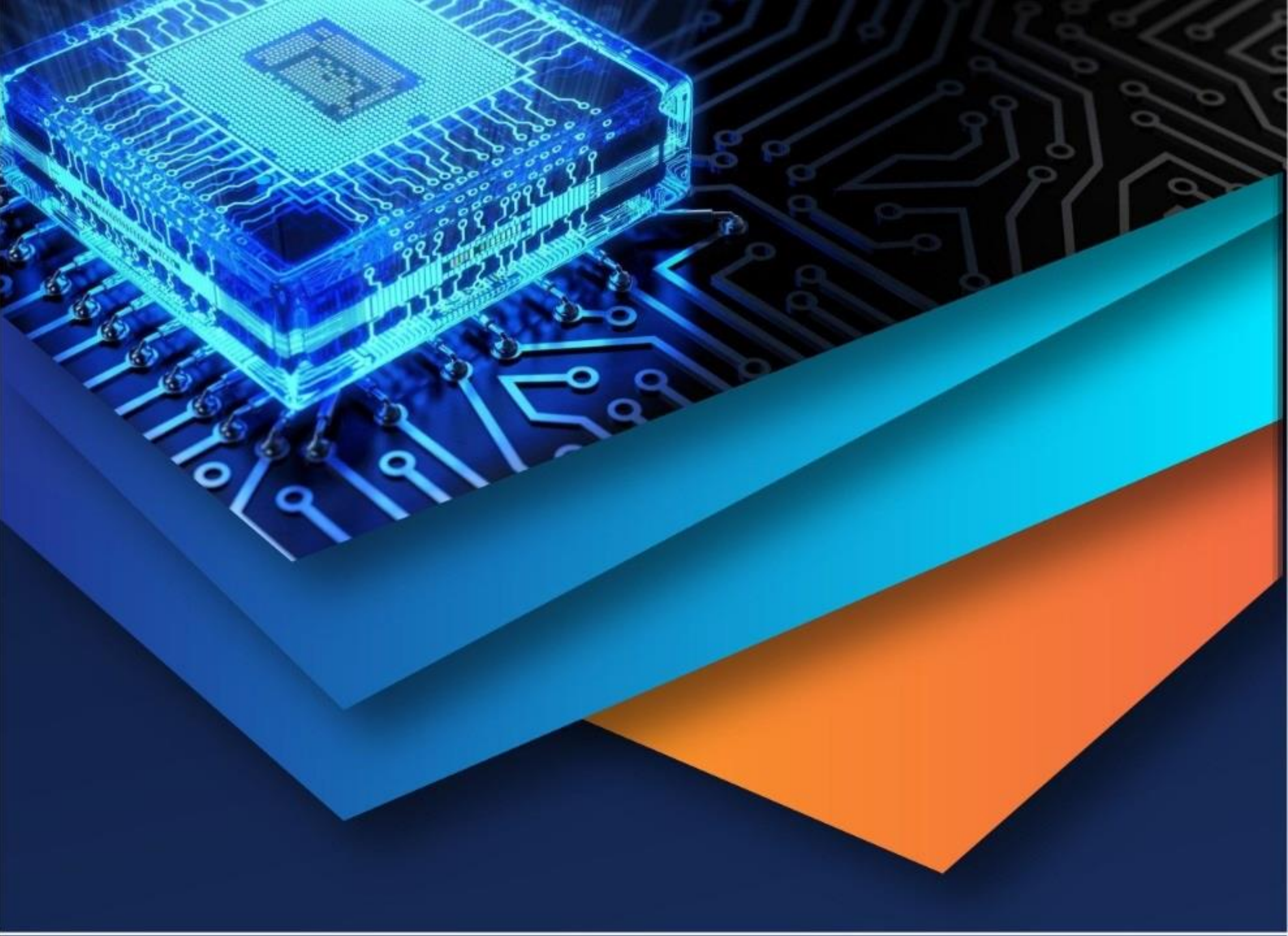

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