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Disease Detection of Apple with the Help of Image Processing

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ABSTRACT:

Apple farming is significant to world fruit production and rural economies, particularly in temperate countries. Yet apple crops are commonly infested with several fungal and bacterial diseases like scab, rot, and blotch that can decrease both yield and quality considerably. Manual detection of the disease is tedious, subjective, and prone to errors, thus resulting in late diagnosis and misapplication of medication.

This study proposes an end-to-end image-processing-based deep learning architecture intended to detect and classify apple diseases automatically into four classes: Healthy Apple, Scab Apple, Rot Apple, and Blotch Apple. The framework utilizes the capability of Convolutional Neural Networks (CNNs) for classification and feature extraction, providing a non-invasive, scalable, and precise way for real-time disease monitoring. A filtered dataset of tagged images of apples were employed for training and testing with accuracy, precision, recall, and F1-score as performance metrics. The model was also compared with standard ML models and improved using transfer learning.

Our findings show that the system can attain high classification accuracy and can be successfully implemented in real-world farming environments through mobile applications or IoT platforms, thus supporting precision agriculture and sustainable farming practices.

Keywords: Apple Disease Detection, Image Processing, Deep Learning, CNN, Precision Agriculture, Plant Pathology, Smart Farming, MobileNetV2, ResNet50, Transfer Learning, IoT, AgriTech

INTRODUCTION:

Apples are the most widely consumed fruits in the world, and commercial cultivation is both economically and nutritionally significant. Yet, apple crops are susceptible to a number of diseases resulting from infections by pathogens like Venturia inaequalis (scab), Botrytis cinerea (rot), and blotch-causing bacteria. These diseases generally have characteristic visual symptoms such as lesions, spots, or discoloration, which can be recorded and analyzed through digital images.

Conventional disease detection is based on experienced visual examination, which is subjective and usually impractical for extensive monitoring. The advent of AI and deep learning technologies allows objective and automated evaluation of crop health. CNNs, especially, are good at extracting spatial patterns from images and are thus extremely well-suited for detecting plant diseases based on leaf or fruit images.

This research focuses on developing a strong image classification model based on CNNs and transfer learning methods to detect apple diseases based on images. The objective is to provide farmers, agricultural researchers, and supply chain players with fast and accurate disease detection, utilizing equipment available through smartphones and cloud interfaces.

DATASET:

The dataset employed in this research is named "Apple Diseases" and comprises more than 2,000 high-resolution images of four classes:

Healthy Apple Scab Apple Rot Apple Blotch Apple
Image Sources:
Open-source datasets (PlantVillage, AI Challenger) Field photography by collaborating farmers Annotated images verified by agricultural experts
Preprocessing:
Image Resizing: All images resized to 224×224 pixels Normalization: Pixel values scaled between 0 and 1
Data Augmentation: To increase dataset diversity and mitigate overfitting, operations such as:

Rotation (±30°)
Horizontal & vertical flipping Random zooming Brightness adjustments
Dataset Split:
Training Set: 80%

Validation Set: 10%

Testing Set: 10%

In spite of class imbalance, oversampling (e.g., SMOTE) was not applied since there was strong augmentation and ample generalization.

METHODOLOGY:

1.1 Image Preprocessing

Resized, normalized, and augmented images ready through OpenCV and TensorFlow ImageDataGenerator

1.2 CNN Architecture:

A CNN was created in-house with the following layers:

Conv2D (32 filters, 3x3) → ReLU → MaxPooling Conv2D (64 filters) → ReLU →

MaxPooling Flatten → Dense (128 neurons) → Dropout (0.5) Dense output layer with

Softmax (4 classes)

1.3 Transfer Learning:

Along with a tailored CNN, two state-of-the-art pre-trained models were experimented with:

MobileNetV2 ResNet50

Top layers were fine-tuned on the apple dataset, minimizing training time while increasing accuracy.

1.4 Training Configuration:

Optimizer: Adam Learning Rate: 0.001

Loss Function: Categorical Crossentropy Epochs: 300

Batch Size: 32

ALGORITHMS USED:

CNN: Main architecture for disease detection

Transfer Learning: Used MobileNetV2 and ResNet50 for faster training

SVM with HOG Features: Baseline ML model, underperformed due to limited feature abstraction

KNN: Alternate baseline for performance comparison

EVALUATION METRICS & RESULTS:

Metrics Used:

Accuracy, Precision, Recall, F1 Score Confusion Matrix for error analysis

Table 1: CNN Performance Overview

Class	Precision	Recall	F1 Score
Healthy Apple	93.2%	95.1%	94.1%
Scab Apple	91.4%	90.6%	91.0%
Rot Apple	88.9%	87.5%	88.2%
Blotch Apple	90.5%	89.2%	89.8%
Overall	91.0%	90.6%	90.8%

CONCLUSION:

The model revealed a high level of capability for the diagnosis of apple diseases precisely from image data alone. Using CNNs worked very effectively to perform this operation. The technology provides farmers and agricultural specialists with an easy, user-friendly mechanism to aid early detection, reduce yield loss, and lower the use of chemicals through precision therapy.

The approach can be applied on smartphones or cloud platforms in order to bring it to everyone's reach, especially in those rural areas which are resource-deprived.

LIMITATIONS & ETHICAL CONSIDERATIONS:

Challenges:

Real-world lighting/background variation not exhaustively tested Under-representation of rare disease variations

Ethical Concerns:

User privacy: Risks with uploading sensitive farm data Over-reliance: Risk of bypassing expert

advice Mitigation:

Local inference with on-device processing Model explainability tools

Transparent feedback and user control

SYSTEM ARCHITECTURE & MODULES:

Frontend: ReactJS interface for image upload Backend: Flask API for model inference

Model Server: TensorFlow runtime; ONNX supported Database: MongoDB for metadata and prediction history

Real-Time Queue: Redis/Kafka for streaming (optional)

Tech Stack
Python, OpenCV, TensorFlow, Keras

REAL-WORLD APPLICATIONS:

Farmers' mobile disease detection tools Orchard monitoring using drones

Fruit grading in the supply chain

Government crop monitoring for early warning

FUTURE SCOPE:

- IoT Integration: Integrate weather and soil information with visual inputs Severity Analysis: Predict damage levels for treatment purposes
- Edge Device Optimization: Raspberry Pi or Jetson Nano deployment Voice-Based Support: Multilingual AI assistants
- XAI Integration: Model transparency for farmer trust Blockchain Traceability: Share disease reports in agri-networks
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