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Project Synopsis

on

Crop Disease Detection and Price Prediction

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in

Computer Science & Engineering

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1. Abstract -

Crop diseases and volatile market prices are two major challenges that reduce farmer incomes and food security. This project proposes an end-to-end AI system combining

(1) an image-based Crop Disease Detection Module using lightweight convolutional neural networks (MobileNet/ResNet variants) to classify disease type and estimate severity from leaf/fruit/stem photos, and

(2) a Crop Price Prediction Module using time-series models (LSTM/GRU) and ensemble regressors (XGBoost/Random Forest) to forecast near-term market prices using historical AgMarknet/FAO data plus weather and seasonal features. A web application (React frontend + Flask REST API) will enable farmers to upload images, view disease diagnosis and treatment advice, and receive market-price forecasts with recommended selling windows and markets. The system aims to improve crop health interventions and maximize selling price, delivering measurable economic benefit to farmers.

2. Introduction -

Agricultural productivity in India and many parts of the world is constrained by timely disease detection and inefficient market decisions. Smallholder farmers often lack access to rapid diagnostic services and reliable market forecasting — leading to yield losses and suboptimal sales timing. Integrating computer vision and time-series forecasting into a farmer-facing application can address both agronomic and economic needs.

Problem Statements

- *Problem 1:* Farmers detect crop diseases too late due to lack of diagnostic tools and awareness, causing yield loss.
- *Problem 2:* Farmers often sell produce at low prices because they lack price forecasts or market recommendations.

Project Objectives

1. Build a robust image-classification model to detect common crop diseases and estimate severity from smartphone images.
2. Build an accurate price prediction pipeline using historical price data and exogenous features (seasonality, rainfall, nearby market trends).
3. Provide actionable outputs to farmers: disease diagnosis + treatment recommendation, and price forecasts + suggested selling time/market.
4. Deploy a web application with REST APIs for service access and a database to store user history and model outputs.

Scope & Deliverables

- Single-page responsive web frontend (React) for farmers to upload images and view advisories.
- Flask-based REST APIs: /detect-disease and /predict-price.
- Trained and evaluated ML models for disease detection and price prediction, with sample datasets and performance reports.
- A project report and codebase with instructions for deployment.

Technical Terms

- *CNN:* Convolutional Neural Network used in image classification.
- *LSTM/GRU:* Recurrent neural network architectures for time-series forecasting.
- *AgMarknet:* Indian government market price dataset for agricultural commodities.

3. Literature Survey -

Computer Vision for Plant Disease Detection

- PlantVillage (Hughes & Salathé) introduced a large dataset used widely for leaf disease classification. Many studies report high accuracy with deep CNNs (ResNet, Inception) when trained on controlled imagery.
- Recent work focuses on mobile-friendly architectures (MobileNet, EfficientNet-lite) and domain adaptation to field images taken under natural light and background variation.
- Severity estimation (percent leaf area affected) is commonly tackled using segmentation models (U-Net) or regression heads on classification CNNs.

Price Prediction in Agriculture

- Time-series models (ARIMA, SARIMA) have been used historically for commodity price forecasting.
- Deep learning models (LSTM, GRU) and gradient boosting (XGBoost, LightGBM) show improved performance when combining historical prices with exogenous features like rainfall, temperature, and market arrival volumes.
- Combining multiple nearby market prices and using hierarchical forecasting techniques improves regional recommendation accuracy.

Integrated Systems & Farmer-Facing Apps

- Several mobile apps offer either disease identification or price alerts, but integrated systems combining both agronomic and economic advisories are less common.
- Challenges include noisy field images, limited labeled local data, and heterogeneity of market microstructures.

Gap Analysis & Contribution

- Existing models often perform well on benchmark datasets but degrade on in-field photos. This project will emphasize data augmentation, transfer learning from PlantVillage, and optional collection of local images to fine-tune models.
- The novelty is in coupling disease diagnosis with price forecasting to provide end-to-end decision support for farmers.

4. Methodology -

Disease Detection Module

1. *Data Collection & Preprocessing:* Use PlantVillage; optionally fine-tune with locally collected images. Resize images, normalize, apply augmentations (rotation, brightness, cropping).
2. *Model Selection & Training:* Start with Transfer Learning (MobileNetV2 / ResNet50). Train classifier for disease classes + healthy label. Add a regression head or separate model to estimate severity.
3. *Evaluation Metrics:* Accuracy, Precision, Recall, F1-score for classification; mean absolute error (MAE) for severity.
4. *Explainability & Advice:* Use Grad-CAM for visual explanation and map disease to a set of treatment suggestions (organic/pesticide/irrigation) stored in a rule-based lookup.

Price Prediction Module

1. *Data Ingestion:* Ingest AgMarknet historical price data, weather/rainfall (public APIs), and local market features.
2. *Feature Engineering:* Lag features, rolling means, seasonality indicators, crop cycles, and weather variables.
3. *Modeling:* Compare ARIMA baseline, LSTM/GRU models, and tree-based regressors (XGBoost). Ensembling or model selection via cross-validation.
4. *Evaluation Metrics:* RMSE, MAE, MAPE. Backtest predictions and assess recommended selling windows.

Web App & Backend

- *API Design:* /api/detect (POST image, returns disease, severity, advice), /api/predict (POST crop, location, returns price forecast & market suggestion).
- *Database:* PostgreSQL for structured records; images stored in object storage or file system with references in DB.
- *Frontend:* Simple React UI for uploads and dashboards.

5. Facilities Required for Proposed Work -

Software:

- Python 3.9+
- TensorFlow / Keras or PyTorch
- scikit-learn, XGBoost, pandas, numpy
- Flask / Django REST framework
- React, Node.js, Bootstrap
- PostgreSQL or MongoDB

Hardware:

- Development laptop (8+ GB RAM) for frontend/backend work
- GPU-enabled machine (NVIDIA GPU with CUDA support) for model training (cloud GPU or local workstation) — recommended but small models / transfer learning can be done on CPU for prototypes.
- Optional: Smartphone(s) for capturing in-field images and testing the frontend.

6. References -

[1] S. P. Hughes and D. P. Salathé, "An open access repository of images on plant disease for the research community," arXiv preprint arXiv:1511.08060, 2015.

[2] Indian Government, AgMarknet, "National Agriculture Market", available: https://agmarknet.gov.in (accessed 2024).

[3] FAO, "FAOSTAT — Food and Agriculture Data", available: https://www.fao.org (accessed 2024).

[4] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, 2012.

[5] F. Chollet, Deep Learning with Python, Manning Publications, 2018.