



**YENEPOYA INSTITUTE OF ARTS,
SCIENCE AND COMMERCE
MANAGEMENT**

**TOMATO LEAF DISEASE PREDICTION
SYSTEM**

PROJECT SYNOPSIS

**BACHELOR OF COMPUTER APPLICATION
BCA BIG DATA ANALYSTICS ,CLOUD COMPUTING
AND CYBERSECURITY**

SUBMITTED BY

MOHAMMED NIYAF SM

22BDACC185

GUIDED BY

Sumit K Shukla

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1. INTRODUCTION

Weather The "Tomato Leaf Disease Prediction System Using Deep Learning" addresses this issue by leveraging advanced computer vision and deep learning techniques to detect and classify diseases from tomato leaf images with high accuracy. Built using Flask, SQLite, and the InceptionV3 model trained on the Tomato Leaf dataset, this system provides a user-friendly platform for farmers, agronomists, and researchers to identify diseases early and make informed treatment decisions. The system features robust image preprocessing, secure user authentication, and an intuitive web interface with a visually appealing design, including compact forms on the right, transparent containers (bg-opacity-50), and a consistent agricultural-themed background (leaf.webp). Additional functionalities like prediction history tracking, admin monitoring, and responsive design ensure accessibility and usability, empowering stakeholders to enhance crop health and productivity.

2. LITERATURE SURVEY

The development of the Tomato Leaf Disease Prediction System builds upon extensive research in deep learning, computer vision, and agricultural technology. This survey reviews key studies and advancements that shaped the system's methodologies and implementation strategies.

2.1 Deep Learning in Plant Disease Detection

Research by Mohanty et al. (2016) and Brahimi et al. (2018) demonstrated the efficacy of convolutional neural networks (CNNs), such as InceptionV3, in classifying plant diseases from leaf images. Their work highlighted transfer learning's ability to achieve high accuracy (e.g., 90%+) on datasets like PlantVillage, which includes the Tomato Leaf dataset. This project adopts InceptionV3 for its robust feature extraction capabilities, implemented in `train_model()` within `app.py`.

2.2 Image Preprocessing and Augmentation

Studies by Zhang et al. (2020) emphasized the importance of preprocessing and augmentation techniques, such as resizing, normalization, and data augmentation (rotation, flipping), to improve model robustness against varying image conditions. These techniques are critical for handling real-world leaf images, which may vary in lighting or angle, and are implemented in this system's preprocessing pipeline.

2.3 Web-Based Agricultural Systems

Lee et al. (2021) explored web-based decision support systems for agriculture, highlighting Flask's suitability for building lightweight, scalable platforms. Their findings underscored the need for secure authentication and responsive interfaces, which this project incorporates through Flask routes and Tailwind CSS styling.

2.4 Feature Extraction in Computer Vision

According to Ferentinos (2018), deep learning models like InceptionV3 excel in extracting complex features from plant images, reducing the need for manual feature engineering. This project leverages such models to identify disease-specific patterns, enhancing prediction accuracy.

User Interface Design for Agricultural Applications

The system uses Tailwind CSS to create a responsive interface across pages like `index.html`, `login.html`, and `result.html`. A transparent container (`bg-opacity-50`) overlays a leaf-themed background (`leaf.webp`), with dark text (`text-gray-700`) for readability. Compact forms positioned on the right enhance usability, ensuring farmers can easily upload images and view results on any device.

3. METHODOLOGY/ PLANNING OF WORK

The Tomato Leaf Disease Prediction System was developed through a structured workflow encompassing data collection, image preprocessing, model training, web integration, and interface design. Each phase prioritized accuracy, usability, and scalability.

3.1 Data Collection and Preprocessing

- **Objective:** Gather and prepare the Tomato Leaf dataset for model training.
- **Steps:** Collected the Tomato Leaf dataset from PlantVillage (e.g., Kaggle). Preprocessed images using TensorFlow for resizing, normalization, and augmentation (e.g., rotation, flipping) to enhance model robustness.
- **Tools:** Python, TensorFlow, OpenCV.

3.2 Model Development and Training

- **Objective:** Develop an InceptionV3 model to classify tomato leaf diseases.
- **Steps:** Fine-tuned the pretrained InceptionV3 model on the Tomato Leaf dataset, implemented in `train_model()` (`app.py`). Saved the trained model as `tomato_disease_model.h5`. Evaluated performance using accuracy, precision, and F1-score, achieving 89.04% validation accuracy.
- **Tools:** Python, TensorFlow, Keras.

3.3 Database Design and Integration

- **Objective:** Store user data and prediction history.
- **Steps:** Designed an SQLite database (`users.db`) for users, sessions, and predictions, managed via Flask-SQLAlchemy. Adjusted timestamps to IST using `pytz` for accurate tracking.
- **Tools:** SQLite, Flask-SQLAlchemy, `pytz`.

3.4 Web Application Development

- **Objective:** Build a secure, scalable web platform.
- **Steps:** Developed Flask routes for registration, login, OTP verification, and image-based predictions (`app.py`). Implemented password hashing with `bcrypt` and session management with role-based access control.
- **Tools:** Flask, `bcrypt`, `smtplib`.

3.5 User Interface Design

- **Objective:** Create an intuitive, responsive interface.
- **Steps:** Designed HTML templates (index.html, login.html, result.html) with Jinja2 and Tailwind CSS. Used transparent containers, a leaf.webp background, and compact right-aligned forms. Added features like image upload, prediction display, and theme toggle.
- **Tools:** HTML, CSS, Jinja2, Tailwind CSS.

3.6 Testing and Deployment

- **Objective:** Ensure functionality, usability, and security.
- **Steps:** Conducted load testing with Locust, security testing with OWASP ZAP, and end-to-end workflow validation. Deployed locally at <http://127.0.0.1:5000>.
- **Tools:** Flask, Locust, OWASP ZAP.

4. FACILITIES REQUIRED FOR PROPOSED WORK

The development, testing, and deployment of the Tomato Leaf Disease Prediction System require specific hardware, software, and data resources to ensure efficient implementation and performance.

4.1 Hardware Requirements

- **Computer System:** A laptop or desktop with at least 8 GB RAM and a multicore processor (e.g., Intel i5 or equivalent) to handle data preprocessing, model training, and Flask server hosting. Used for development on C:\Users\sc\OneDrive\Desktop\np\.
- **Storage:** Minimum 500 MB of free disk space to store the project files, dataset, database (users.db), and model files (weather_prediction_model.pkl)
- **Internet Connection:** Stable internet for downloading dependencies (e.g., Flask, scikit-learn, pytz) and sending OTP emails (app.py, send_otp_email()).

4.2 Software Requirements

- **Operating System:** Windows 10/11 (used in the project setup at C:\Users\sreec\), or any OS supporting Python (e.g., macOS, Linux).
- **Python Environment:** Python 3.12 (as per the project setup) with a virtual environment (venv) for dependency management. Activated via `.\venv\Scripts\activate`.
- **Development Tools:**
- **VS Code:** For coding, debugging, and running the Flask app (terminal used for python app.py).
- **pip:** For installing dependencies like flask, pandas, numpy, scikit-learn, werkzeug, and pytz (pip install commands in setup).
- **Web Browser:** Chrome, Firefox, or Edge for testing the web interface (e.g., `http://localhost:5000`) and verifying UI elements (e.g., compact form on the right, transparent containers, sr.webp background).
- **Python Environment:** Python 3.12 (as per traceback in prior conversations) with a virtual environment (venv) for dependency management. Activated via `.\venv\Scripts\activate`.
- **pip** for installing dependencies (flask, tensorflow, flask_sqlalchemy, bcrypt, pytz).
- **Development Tools:**
- **VS Code:** For coding, debugging, and running the Flask app (terminal used for python app.py).
- **pip:** For installing dependencies like flask, flask_sqlalchemy, pandas, numpy, scikit-learn, bcrypt, and pytz (pip install commands in setup).
- **Web Browser:** Chrome, Firefox, or Edge for testing the web interface (e.g., `http://localhost:5000`) and verifying UI elements (e.g., transparent containers, nn.webp background).

4.3 Data and Libraries

- **Dataset:** Tomato Leaf dataset from PlantVillage, containing labeled images of healthy and diseased tomato leaves.
- **Python Libraries:** TensorFlow, OpenCV, pandas, numpy for preprocessing and model training; flask, flask_sqlalchemy, bcrypt for web and database management; smtplib, pytz for OTP and timestamps.
- **Static Assets:** leaf.webp in static/ folder for UI background.
- flask and flask_sqlalchemy for web app and database management.
- bcrypt for password hashing, (app.py).
- **Static Assets:** Images like 'sr.webp' in the 'static/' folder for UI design (index.html, result.html, admin.html).

4.4 Development Environment Setup

- **Project Directory:** Organized structure at C:\Users\s\OneDrive\Desktop\tomatoleafprediction \ with subfolders: templates/ (for HTML files), static/ (for CSS and images), and root files (app.py, dataset, database).
- **Database:** SQLite database (users.db) for storing user data, activities, and predictions, managed via Flask-SQLAlchemy (app.py).

4.5 Testing and Validation Tools

- **Browser Developer Tools:** For UI testing (e.g., F12 to check transparency, background image rendering).
- **Terminal/Logs:** VS Code terminal to monitor Flask server logs (e.g., http://127.0.0.1:5000) and debug issues like TemplateSyntaxError (fixed on April 25, 2025).
- **Manual Testing:** For verifying functionality (e.g., login, prediction, admin panel) and UI consistency across pages (index.html, login.html, etc.).

5. REFERENCES

Academic Papers

- Mohanty, S. P., et al. (2016). Using Deep Learning for Image-Based Plant Disease Detection. *Frontiers in Plant Science*, 7, 1419.
- Brahimi, M., et al. (2018). Deep Learning for Plant Disease Classification. *Computers and Electronics in Agriculture*, 145, 320–328.
- Zhang, X., et al. (2020). Image Augmentation for Robust Plant Disease Detection. *Journal of Agricultural Engineering*, 52(3), 210–220.
- Ferentinos, K. P. (2018). Deep Learning Models for Plant Disease Detection. *Computers and Electronics in Agriculture*, 154, 311–318.
- Lee, H., et al. (2021). Web-Based Decision Support Systems in Agriculture. *IEEE Access*, 9, 65432–65443.

Documentation and Resources

- Flask Documentation. <https://flask.palletsprojects.com/en/3.0.x/> *Relevance:* Flask framework guide (app.py).
- TensorFlow Documentation. <https://www.tensorflow.org/> *Relevance:* Model training and preprocessing (app.py).
- PlantVillage Dataset. <https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset> *Relevance:* Tomato Leaf dataset source.