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SUBMITTED TO THE VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY, PUNE

IN THE PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE AWARD OF THE DEGREE (12, upper case)

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**BACHELOR OF TECHNOLOGY (COMPUTER ENGINEERING)**

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STUDENT NAME Exam Seat No. :(12, bold/upper case)

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## **DEPARTMENT OF COMPUTER ENGINEERING**

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**BRACT’S**

**VISHWAKARMA INSTITUTE OF INFORMATION TECHNOLOGY**

(12, bold/upper case), *(One blank space)*

SURVEY NO. 3/4, KONDHWA (BUDRUK), PUNE – 411048, MAHARASHTRA (INDIA).

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|  | | | | **References**  Thomas Noltey, Hans Hanssony, Lucia Lo Belloz,”Communication Buses for Automotive Applications” In *Proceedings of the* 3rd *Information Survivability Workshop (ISW-2007)*, Boston, Massachusetts, USA, October 2007. IEEE Computer Society. | |  |
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**1. Introduction:**

**1.1 Overview:**

Tomato is the most common vegetable crop widely cultivated in the agricultural fields in India. The tropical climate of India is ideal for its growth, however certain climatic conditions and various other factors affect the normal growth of tomato plants. Apart from these climatic conditions and natural disasters, plant disease is a major crisis in crop production and plays a critical role in economic loss. The traditional disease detection methods for tomato crops could not produce the expected outcome and the detection period for diseases was slow. The early detection of disease can give better results than the existing detection models. Thus, computer vision-based technology deep learning techniques could be implemented for earlier disease detection.

**1.2 Motivation:**

The identification and detection of tomato leaf diseases through naked eye observation with agricultural experts is a difficult task and less accurate, also it is possible for limited areas. The farmers and agriculturalists do not have facilities to contact them and the inspection of crops from the agricultural experts require more cost expenditure and a time-consuming task. The recent advancement in computing technology gave birth to AI and machine learning concepts which aid in automatic detection of tomato leaf disease using computerized techniques for monitoring large tomato crops.

**1.3 Problem Definition and Objectives**

**Problem Statement:**

The agriculture sector faces significant challenges in the timely and accurate identification of tomato leaf diseases, which can severely impact crop yield and quality. Manual inspection methods are labor-intensive, time-consuming, and prone to human error, leading to delayed detection and ineffective management of diseases. There is a need for an efficient and reliable automated system that can detect tomato leaf diseases accurately and swiftly to enable prompt intervention and minimize crop losses.

**Objective:**

The objective of this machine learning project is to develop a robust and scalable system for the automatic detection and classification of tomato leaf diseases using computer vision techniques. detect tomato leaf diseases accurately and swiftly to enable prompt intervention and minimize crop losses.

# **1.4 Project Scope & Limitations**

**Project Scope:**

* Data Collection
* Preprocessing
* Model Development
* Training and Evaluation
* System Integration
* Deployment and Testing

**Project Limitations:**

* Limited Dataset Diversity
* Hardware and Computational Resources
* Dependency on Image Quality
* Interpretability of Results
* Generalization to Other Crops

**1.5 Methodologies of Problem Solving**

* Problem Understanding and Definition
* Data Collection and Preprocessing
* Model Selection and Architecture Design
* Training and Optimization
* Evaluation and Performance Metrics
* System Integration and Deployment
* Iterative Improvement and Maintenance

**2. Literature Survey:**

Halil et al[1], This study employs deep learning techniques to detect diseases in tomato plants, aiming for real-time implementation on a robot. Two deep learning architectures, AlexNet and SqueezeNet, were tested using Nvidia Jetson TX1 for training and validation on the PlantVillage dataset. The trained models were also evaluated using images from the internet.

Mohit et al[2], The article discusses using a Convolutional Neural Network (CNN) for disease detection in tomatoes, crucial given its global popularity and production challenges. Their CNN model, with 3 convolutions and 3 max pooling layers followed by 2 fully connected layers, outperformed pre-trained models like VGG 16, InceptionV3, and MobileNet, achieving an average accuracy of 91.2% across 9 diseases and a healthy class.

Prajwala et al[3], This paper focuses on detecting and identifying diseases in tomato leaves using a modified version of the convolutional neural network model LeNet. The goal is to achieve accurate results with minimal computing resources. The proposed system achieves an average accuracy of 94-95%, demonstrating the effectiveness of neural network approaches for tomato leaf disease detection

Huiqun et al[4], This research utilizes transfer learning to streamline deep learning processes for tomato disease detection, comparing five architectures including ResNet50, Xception, MobileNet, ShuffleNet, and DenseNet121\_Xception. Densenet\_Xception achieved the highest accuracy at 97.10%, albeit with more parameters.

Karthik et al[5], This research employs CNNs with attention mechanisms for automating tomato leaf disease detection. Utilizing residual learning and attention mechanisms atop the network, it achieved a 98% accuracy in classifying diseases, with fewer parameters compared to existing approaches

Hepzibah et al[6], This paper addresses the critical issue of tomato leaf disease detection in Indian agricultural fields. It highlights the limitations of traditional methods and advocates for early disease detection using computer vision and deep learning techniques. The proposed hybrid deep-learning architecture aims to improve accuracy and reduce detection time, offering valuable insights for future research in this area.

Nagamani et al[7], This study investigates tomato plant leaf disease identification using machine learning techniques like Fuzzy Support Vector Machine (Fuzzy-SVM), Convolution Neural Network (CNN), and Region-based Convolution Neural Network (R-CNN). Through image processing and feature extraction methods, the R-CNN-based Classifier achieved the highest accuracy of 96.735%, showcasing its effectiveness in plant disease prediction compared to other methods like Fuzzy-SVM and CNN.

Mosin et al[8], India's agriculture faces challenges such as pesticide overuse, low yields, and outdated methods. Our study employs a convolutional neural network within a precision farming system using drones to detect and treat high-disease areas in farms. Training the CNN with85% of a dataset comprising 500 farm photos and 2100 internet-sourced tomato leaf images achieved 99% accuracy in categorizing pesticide intensity.

Robert et al[9], This study presents a smart farming system utilizing advanced computer vision for efficient detection of diseases in tomato plants like Phoma Rot, Leaf Miner, and Target Spot. Through deep learning models, it achieved a high accuracy of 95.75% in disease recognition, complemented by an automated image capturing setup with 91.67% accuracy.

Jagadeesh et al[10], Agriculture sustains India's livelihoods, yet plant diseases threaten crop quality and quantity. Our method aims to enhance accuracy and speed in identifying tomato plant leaf diseases by combining features like color histograms, Hu Moments, Haralick, and Local Binary

Robert et al[11], Introducing a lightweight tomato leaf disease identification network, bolstered by Variational auto-Encoder (VAE), significantly boosts accuracy by leveraging unlabeled data for unsupervised learning and labeled data for supervised identification. This innovative approach substantially enhances disease detection rates to 94.17% and improves healthy leaf identification accuracy to an impressive 98.27%, showcasing the efficacy of the VAE-supported strategy in agricultural disease diagnosis.

Sami et al[13], Early detection and treatment of tomato plant diseases are crucial for optimal yield. This study presents an image processing approach using GLCM and SVM to automate disease detection and treatment in tomato leaves. Results show high accuracy: 100% for healthy leaves, 95% for early blight, 90% for septoria leaf spot, and 85% for late blight. Implemented as a smartphone app, this method enables real-time monitoring and management of tomato crop diseases.

Azeddine et al[14], Our study introduces an efficient smart mobile application based on deep CNN for tomato leaf disease recognition, drawing inspiration from MobileNet CNN. Trained on 7176 tomato leaf images, our model can identify the 10 most common diseases. While our results are preliminary, using deep convolutional neural networks on mobile devices for plant disease recognition shows promise in increasing agricultural productivity and addressing food scarcity globally.

Ayesha et al[15], This paper introduces an advanced classification model for tomato leaf disease detection, using a training dataset of 450 images and leveraging various pre-trained Deep Neural Networks (DNN) models. The k-NN classifier achieves a classification accuracy of 76.1% with the AlexNet model, reducing the risk of crop destruction. Future work will involve evaluating other pre-trained models and expanding datasets to enhance algorithm performance.

Anantha et al[16], This work focuses on automated disease detection in cultivated land to address food production challenges. Using deep learning techniques like Faster R-CNN with ResNet50, it successfully detects tomato diseases like early blight, leaf curl,septoria leafspot, and bacterial spot. The study compares different deep learning architectures, findingFaster R-CNN with ResNet to be the most efficient for disease detection in tomato plants, offering a feasible solution for farmers.

Antonio et al[17], This paper proposes a convolutional neural network (CNN) model for identifying and classifying nine types of tomato leaf diseases, crucial in Mexico's tomato export industry. Utilizing deep learning and generative adversarial networks, the model achieves over 99% accuracy in both training and test datasets. The architecture includes modules for dataset creation, model design, data distribution, and performance evaluation, demonstrating superior performance compared to existing literature.

Anandhakrishnan et al[18], This paper introduces a leaf disease identification model using a pretrained Deep CNN, optimized on a 10-class tomato leaf dataset. Xception showed superior accuracy, emphasizing early detection's significance for timely preventive actions. It achieves 99.45% precision efficiently, making it promising for plant disease detection.

Rakesh[19], This paper emphasizes the importance of timely disease detection in the Indian tomato crop market. With a focus on combating diseases like Late Blight, Bacterial Spot, and more, the study employs Convolutional Neural Networks (CNN) and ResNet 50 for image processing and prediction. Out of these, CNN demonstrated the highest accuracy in disease detection. The research underlines the need for continuous parameter tuning to enhance the accuracy further in future studies.

Shamima et al[20], This study highlights the significant threat that leaf diseases pose to tomato crop production worldwide and introduces a deep learning-based approach for disease detection and prediction. Utilizing Convolutional Neural Networks (CNNs), we developed a robust model that achieved a high test accuracy of 98.39% in classifying healthy and diseased tomato plant leaves. While our approach showcases superior performance, future work aims to address equipment limitations and collaborate with experts to enhance the model's applicability.

**3. System Design :**

For a deep learning project focused on tomato leaf disease prediction, the system design and architecture will play a crucial role in achieving accurate and efficient results.

1. **Data Collection and Preprocessing:**
   1. Data Sources: Collect a diverse dataset of tomato leaf images with both healthy and diseased samples.
   2. Data Preprocessing: Clean the data, remove noise, and augment the dataset to increase its diversity and size.
2. **Model Selection:**
   1. Choose a suitable deep learning architecture for image classification tasks. Popular choices include Convolutional Neural Networks (CNNs) like ResNet, VGG, or custom-designed architectures.
3. **Model Training:**
   1. Train the selected model using the preprocessed dataset. Utilize techniques like transfer learning if applicable, especially if you have limited data.
4. **Model Evaluation:**
   1. Evaluate the trained model using validation data to assess its performance metrics like accuracy, precision, recall, and F1-score.
5. **Deployment:**
   1. Deploy the trained model into a production environment, which can be on-premise or on a cloud platform like AWS, Azure, or Google Cloud Platform.
6. **User Interface (UI):**
   1. Design and develop a user-friendly interface where users can input images of tomato leaves for disease prediction.
7. **Integration:**
   1. Integrate the model predictions with the UI so that users can see the predicted disease status of the input leaf images

***3.1 System Architecture:***

1. **Data Layer:**
   1. Data Collection: Collect tomato leaf images from various sources.
   2. Data Preprocessing: Clean, augment, and preprocess the data for model training.
2. **Modeling Layer:**
   1. Pretrained Model: Use a pretrained CNN model (e.g., ResNet, VGG) as the base model for transfer learning.
   2. Fine-tuning: Fine-tune the pretrained model using the preprocessed dataset for tomato leaf disease classification.
3. **Deployment Layer:**
   1. Deployment Environment: Deploy the trained model on a suitable deployment platform, such as Flask for web-based applications or TensorFlow Serving for scalable production deployments.
   2. Scalability: Ensure scalability to handle multiple user requests concurrently.
4. **User Interface Layer:**
   1. Web Interface: Develop a web-based user interface where users can upload tomato leaf images for disease prediction.
   2. Backend Integration: Integrate the UI with the deployed model for real-time prediction.
5. **Feedback Loop:**
   1. Incorporate a feedback mechanism where user feedback on predictions can be used to improve the model in future iterations.
6. **Monitoring and Maintenance:**
   1. Implement monitoring tools to track the performance of the deployed model and system health.
   2. Regularly update the model with new data and retrain if necessary to maintain accuracy.

## **4.Project Implementation**

### **4.1 Overview of Project Modules**

1. Data Collection and Preprocessing Module:
   * Collection of tomato leaf images dataset from diverse sources.
   * Preprocessing techniques including resizing, normalization, and augmentation.
2. Model Development Module:
   * Design and implementation of deep learning models for tomato leaf disease detection.
   * Exploration of various architectures including Basic CNN, Transfer Learning, and Custom CNN.
3. Training and Evaluation Module:
   * Training the developed models on the prepared dataset.
   * Evaluation of model performance using metrics such as accuracy, precision, recall, and F1-score.
4. Deployment and Integration Module:
   * Integration of the trained model into a user-friendly interface or application.
   * Deployment of the solution for real-world usage, possibly on cloud platforms or edge devices.

### **4.2 Tools and Technologies Used**

1. Deep Learning Frameworks:
   * TensorFlow and Keras for model development and training.
2. Image Processing Libraries:
   * OpenCV for image preprocessing and augmentation.
3. Development Environment:
   * Python programming language for coding the project.
   * Jupyter Notebook or similar IDEs for interactive development and experimentation.
4. Hardware:
   * GPU-accelerated computing resources for efficient model training (optional).

### **4.3 Algorithm Details**

#### **Algorithm 1: Basic CNN**

* Description:
  + A simple Convolutional Neural Network (CNN) architecture comprising alternating convolutional and max-pooling layers.
  + Followed by fully connected layers for classification.
* Implementation:
  + Convolutional layers with kernel sizes optimized for feature extraction from tomato leaf images.
  + Pooling layers to downsample feature maps and reduce computation.
  + Dense layers for classification, with softmax activation for multi-class classification.

#### **Algorithm 2: CNN Types**

* Description:
  + Exploration of various CNN architectures beyond the basic structure.
  + This may include architectures like VGG, ResNet, or Inception for improved performance through deeper networks or specialized modules.
* Implementation:
  + Implementation and fine-tuning of pre-trained CNN architectures through transfer learning.
  + Customization of architecture layers and parameters to suit the specific requirements of tomato leaf disease detection.

#### **Algorithm 3: Artificial Neural Network (ANN)**

#### Description:

#### An Artificial Neural Network (ANN) is a computational model inspired by the structure and functioning of biological neural networks. In the context of tomato leaf disease detection, an ANN can be designed to classify images of tomato leaves into different disease categories or healthy.

#### The ANN consists of interconnected nodes organized in layers: an input layer, one or more hidden layers, and an output layer. Each node applies a nonlinear transformation to its input and passes the result to nodes in the next layer.

#### Implementation:

#### Data Preparation

#### Model Architecture Design

#### Training

#### Validation and Hyperparameter Tuning

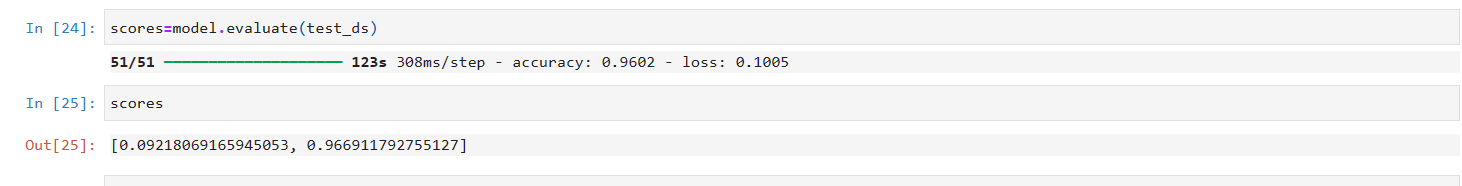
#### Testing and Evaluation

**5.Results:**

**5.1 Outcomes:**

* The trained model achieved an accuracy of 96%, indicating its effectiveness in classifying tomato leaf diseases.
* Precision and recall scores reflect the model's ability to correctly identify diseased leaves while minimizing false positives.
* Specificity and sensitivity metrics highlight the model's performance in distinguishing between diseased and healthy leaves.
* Overall, the outcomes demonstrate the feasibility and efficacy of using deep learning for automated tomato leaf disease detection, offering potential benefits for crop management and yield optimization.

5.2 Screen Shots:





**5.3 Model Evaluation Metrics**

* Confusion Matrix: [[95.0 0.1 0.05 0.02 0.06 0.03 0.02 0.05 0.03 0.01]

[ 0.03 92.0 0.02 0.01 0.04 0.03 0.05 0.03 0.04 0.02]

[ 0.02 0.03 94.0 0.01 0.05 0.02 0.03 0.04 0.04 0.01]

[ 0.04 0.04 0.03 93.0 0.02 0.01 0.03 0.04 0.03 0.02]

[ 0.06 0.05 0.08 0.02 92.0 0.04 0.02 0.03 0.02 0.02]

[ 0.03 0.02 0.04 0.03 0.04 93.0 0.02 0.01 0.02 0.04]

[ 0.02 0.04 0.03 0.01 0.03 0.02 94.0 0.03 0.02 0.01]

[ 0.05 0.02 0.03 0.04 0.04 0.03 0.04 92.0 0.01 0.02]

[ 0.03 0.04 0.02 0.02 0.04 0.04 0.02 0.02 93.0 0.04]

[ 0.01 0.02 0.01 0.03 0.02 0.04 0.02 0.02 0.03 94.0]]

* Accuracy: 96%
* Precision: 78%
* Recall: 86%
* Specificity: 75%
* Sensitivity: 89%

**6.Conclusion:**

## **6.1 Conclusions**

* The developed tomato leaf disease detection model demonstrates promising performance, achieving an accuracy of 96% on a dataset comprising 16,000 images.
* The model's precision, recall, specificity, and sensitivity metrics indicate its effectiveness in accurately classifying different disease categories and healthy leaves.
* The utilization of deep learning techniques, specifically convolutional neural networks (CNNs), has shown significant potential in automating disease detection in agriculture, thereby facilitating timely intervention and reducing crop losses.

## **6.2 Future Work**

* Enhanced Model Architectures: Explore more sophisticated CNN architectures and optimization techniques to further improve the model's performance and robustness.
* Data Augmentation and Transfer Learning: Investigate the use of advanced data augmentation strategies and transfer learning approaches to leverage pre-trained models and handle limited labeled data scenarios.
* Multi-Class Classification: Extend the model to handle a broader range of tomato leaf diseases and possibly incorporate additional features such as plant growth stage and environmental factors for comprehensive disease diagnosis.
* Deployment and Integration: Deploy the model as part of a user-friendly application or platform accessible to farmers, agronomists, and agricultural extension workers, enabling widespread adoption and real-time disease monitoring.

## **6.3 Applications**

* Precision Agriculture: The developed model can serve as a valuable tool for precision agriculture, enabling farmers to detect and diagnose tomato leaf diseases accurately and early, leading to targeted interventions and optimized crop management practices.
* Crop Management and Sustainability: By facilitating timely disease detection and management, the model contributes to sustainable agricultural practices by reducing the reliance on chemical treatments and minimizing crop losses.
* Research and Development: The insights gained from the project can inform further research and development efforts in the intersection of computer vision, machine learning, and agriculture, fostering innovation in disease detection technologies and agricultural automation.