**A Project Report on**

**Multi-Model Deep Learning Fusion for Accurate Plant Disease Detection with Sustainable Treatment Recommendations**

Submitted in partial fulfilment of the requirements for the award of degree

**BACHELOR OF ENGINEERING**

**in**

**ARTIFICIAL INTELLIGENCE & MACHINE LEARNING**

**by**

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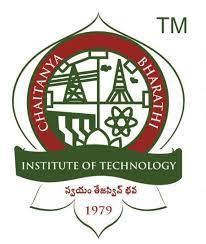
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**CERTIFICATE**

This is to certify that the project titled “**Multi-Model Deep Learning Fusion for Accurate Plant Disease Detection with Sustainable Treatment Recommendations**” is the bonafide work carried out by **Chaduvu Abhinay(160122729028),** **Aaamir Sohail(160122729046),K. Eeswara Vallabh (160122729039)** students of B.E.(AIML) of Chaitanya Bharathi Institute of Technology(A), Hyderabad, affiliated to Osmania University, Hyderabad, Telangana(India) during the academic year 2024-2025, submitted in partial fulfilment of the requirements for the award of the degree in **Bachelor of Engineering in Artificial Intelligence & Machine Learning** and that the project has not formed the basis for the award previously of any other degree, diploma, fellowship or any other similar title.

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**PSO3**. Apply, analyse, design, develop, and test principles of AI concepts on Intelligent Systems.

**Course Objectives**: The aim of course is

1. To explore the literature and formulate a project proposal.
2. To enhance presentation skills and technical writing proficiency.
3. To provide solutions by using modern tools.
4. To Expose Students to Project Based Learning.
5. To effective presentation and documentation.



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**Mini PROJECT:PART-2(22AMC12)**

Course Outcomes: After completion of this course, students will be able to

1. Interpret Literature the purpose of formulating a project proposal.
2. Plan, Analyze, Design and implement a project.
3. Find the solution of an identified problem with the help of modern Technology and give priority to real time scenarios.
4. Plan to work as a team and to focus on getting a working project done and submit a report within a stipulated period of time.
5. Prepare and submit the Report and deliver a presentation.

**CO-PO/PSO Articulation Matrix:**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PO12 | PSO1 | PSO2 | PSO3 |
| CO1 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| CO2 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| CO3 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| CO4 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| CO5 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

**DECLARATION**

I/we hereby declare that the project entitled “**Multi-Model Deep Learning Fusion for Accurate Plant Disease Detection with Sustainable Treatment Recommendations** ” submitted for the B.E (AIML) degree is our original work and the project has not formed the basis for the award of any other degree, diploma, fellowship or any other similar titles.

**Names and Signatures of the Students**

**CHADUVU ABHINAY (160122729028)**

**AAMIR SOHAIL (160122729046)**

**K. EESWARA VALLABH (160122729039)**

**Place:** CBIT-Hyderabad

**Date:**

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The satisfaction that accompanies the successful completion of the task would be incomplete without the mention of the people who made it possible, whose constant guidance and encouragement crown all the efforts with success.

We show gratitude to our honourable Principal **Dr. C. V. Narasimhulu Garu**, for providing all facilities and support.

We are particularly thankful for [**Dr. Y. Ramadevi**](https://www.cbit.ac.in/wp-content/uploads/2023/03/Dr.Y.Ramadevi_CSE_Aug2023.pdf) , the Head of the Department, Department of Artificial Intelligence and Machine Learning, her guidance, intense support, and encouragement, which helped us to mould our project into a successful one.

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We are particularly thankful to our Project Coordinators **Mr. Panduraju Pagidimalla** AssistantProfessor, **Mr.Rathod Sai Vamshi Krishna** Assistant Professor and **Dr. Prabhakar Kandukuri** Professor,Department of Artificial Intelligence and Machine Learning, their guidance, intense support, and encouragement, which helped us to mould our project into a successful one.

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**Abstract**

Plant diseases pose a major challenge to global agriculture, significantly reducing crop yields and threatening food security. These diseases not only lead to large-scale economic losses but also undermine efforts towards sustainable farming. To combat this issue, we present a robust plant leaf disease detection system powered by a **fusion-based deep learning architecture**.

Our proposed method integrates the strengths of **three parallel convolutional branches**—a **simple CNN**, a **deep CNN**, and a **pre-trained EfficientNetB0 model**. Each branch is designed to extract unique and complementary feature representations from input leaf images. While the simple CNN captures basic patterns and textures, the deep CNN learns more complex hierarchical features, and the EfficientNetB0 contributes transfer learning capabilities drawn from its extensive pretraining. These extracted features are then **fused and passed through dense, fully connected layers**, resulting in precise disease classification.

Beyond disease detection, the system incorporates a **pesticide recommendation module** that provides **organic and eco-friendly treatment suggestions** tailored to the identified disease. This integration bridges the gap between accurate AI-driven diagnosis and actionable agricultural advice, promoting sustainable farming practices.

To maximize usability and real-world impact, the solution is deployed as a **responsive web application**. Farmers and users can simply upload images of infected leaves to receive **instant disease identification and organic remedy recommendations**, all in real time.

We validated the model’s performance using large-scale testing on the **Plant Village dataset**, where it demonstrated **exceptional accuracy and reliability**, underscoring the effectiveness of our fusion-based deep learning approach. This system not only enhances the precision of plant disease detection but also empowers users with meaningful, environmentally-conscious guidance—marking a significant step towards intelligent and sustainable agriculture.

**Keywords**

Plant disease detection, deep learning, fusion model, CNN, EfficientNetB0, image classification, sustainable agriculture, organic pesticide recommendation, web application, PlantVillage dataset, real-time diagnosis, feature extraction, precision agriculture, smart farming, convolutional neural networks

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### **1. INTRODUCTION**

Plant diseases remain a significant challenge to global food security, with their impact extending beyond agricultural productivity to the economic stability and well-being of farmers. The ability to identify and treat these diseases at an early stage is crucial in minimizing crop losses, reducing the use of harmful pesticides, and promoting sustainable farming practices. Traditional methods of plant disease detection, which rely heavily on manual inspection, are not only labor-intensive but also prone to errors and inefficiencies, especially in large-scale agricultural settings.

The advent of **artificial intelligence (AI)** has brought transformative changes to the way plant diseases are detected. With the increasing availability of large datasets and advancements in **deep learning** techniques, AI-powered solutions have emerged as effective alternatives to traditional methods. These systems leverage **image processing** and **machine learning algorithms** to automatically identify plant diseases from images of plant leaves or other plant parts, providing quicker and more accurate results.

One of the most promising developments in this field is the use of **convolutional neural networks (CNNs)** and other deep learning models, which are capable of learning complex patterns and features directly from raw image data. These models can automatically extract relevant features from plant images without the need for manual intervention, allowing for high accuracy and robustness in diverse agricultural environments. Furthermore, deep learning-based systems are not constrained by environmental variations such as lighting conditions, plant species, or the quality of the images, making them highly adaptable and scalable.

As AI continues to evolve, these **image-based plant disease detection systems** hold immense potential for revolutionizing agricultural practices. They offer a compelling solution to the challenges of early detection, rapid diagnosis, and the efficient management of plant diseases. With their ability to process large volumes of data quickly and accurately, AI-based solutions can assist farmers in making informed decisions, ultimately improving crop health, productivity, and sustainability across global agricultural systems.

## **1.1 Problem Definition Including the Significance and Objective**

Traditional methods for detecting plant diseases largely depend on **manual visual inspection** and the **expertise of agronomists or pathologists**. While effective in some cases, these approaches are often **labor-intensive**, **subjective**, and susceptible to **human error**, especially when dealing with large-scale agricultural operations. To address these limitations, **machine learning (ML)**—and more specifically, **convolutional neural networks (CNNs)**—has emerged as a powerful tool for automating disease detection by learning intricate patterns and visual cues from plant leaf images.

Despite their promise, single-architecture CNN models frequently struggle to maintain high accuracy in real-world scenarios. Factors such as **inconsistent lighting**, **noisy backgrounds**, **occlusions**, and **varying image resolutions** can degrade their performance. Additionally, many existing solutions are confined to mere **disease classification** and fail to offer **actionable treatment recommendations**, limiting their practical use in guiding farmers toward effective disease management..

**Objective**:

The primary goal of this project is to design and implement a fusion-based deep learning model that leverages the complementary strengths of multiple convolutional neural network (CNN) architectures to enhance the accuracy of plant leaf disease classification. By combining diverse feature representations from different CNN branches, the model aims to achieve robust performance across varied environmental and image conditions. In addition to disease identification, the system is equipped with a functionality to recommend suitable organic pesticide treatments based on the detected disease. This integrated approach not only improves diagnostic precision but also promotes eco-friendly and sustainable agricultural practices by guiding users toward natural, non-chemical solutions.

**1.2 Methodologies:**  
 The methodology adopted for this project comprises several key components, each contributing to the overall functionality and effectiveness of the plant disease detection and recommendation system:

Dataset Selection: The model is trained and evaluated using multiple publicly available datasets to ensure robustness across diverse conditions:

* Plant Village Dataset: Contains approximately [insert number] labeled images of plant leaves captured under controlled lighting and uniform backgrounds, ideal for baseline training.
* Plant Leaves Dataset: Features plant leaf images collected in natural environments, introducing variations in lighting, angles, and backgrounds.
* PlantDoc Dataset (if applicable): Comprises real-world images with significant background clutter, occlusion, and varying illumination, enhancing the model's generalization capabilities in field-like conditions.
* Model Architecture: A fusion-based architecture is developed by integrating three parallel CNN models, each contributing unique feature extraction strengths:
* A Simple CNN is used to capture fundamental textures and low-level visual cues.
* A Deep CNN is employed to learn complex, high-level patterns and hierarchical structures in the leaf images.
* A Pre-trained EfficientNetB0 model is integrated via transfer learning to incorporate generalized visual understanding acquired from large-scale datasets.

The feature outputs from all three branches are concatenated and passed through dense layers, enabling the model to make more informed and accurate disease classifications.

* Pesticide Recommendation:

To enhance the practical utility of the system, a disease-to-treatment mapping module is implemented. This module links each identified disease with corresponding organic pesticide solutions, ensuring environmentally sustainable treatment guidance.

* Deployment:

The final model is deployed as a web-based application designed for user accessibility. The application allows users to upload plant leaf images and receive real-time disease predictions along with tailored organic treatment recommendations, making the system useful for both researchers and farmers in practical settings.

**1.3 Outline of the Results** :

The proposed fusion-based deep learning model demonstrated exceptional performance across various evaluation metrics when tested on the Plant Village dataset. Specifically, the model achieved an accuracy of 98.32%, showcasing its effectiveness in accurately identifying plant diseases. In addition to the high accuracy, the model exhibited strong classification capabilities, achieving:

* Precision: 98.29%, indicating that a very high proportion of the predicted disease cases were indeed correct.
* Recall: 98.28%, reflecting the model's ability to correctly identify most of the true disease cases.

These results underscore the model's robust performance, particularly in controlled environments where the images are of high quality and the conditions are consistent.

The model's success can largely be attributed to the fusion of multiple Convolutional Neural Network (CNN) architectures, which enabled it to extract a rich set of features from the images. By combining the strengths of different CNN models, the system was able to capture a diverse range of characteristics from the input images, such as texture, edges, and color patterns. This fusion of features contributed to the model's strong generalization capabilities, making it well-suited for plant disease detection in ideal conditions.

In summary, the model demonstrated its potential to provide reliable plant disease classification, with strong performance metrics indicating its suitability for further development and potential real-world deployment.

### **1.4 Scope of the Project**

This project addresses two critical challenges in the field of agricultural disease management:

* **Accurate classification of plant diseases**: The system leverages a **multi-model fusion approach** to classify diseases from leaf images, improving diagnosis accuracy through combined feature learning.
* **Eco-friendly pesticide recommendations**: The system also incorporates a **disease-to-treatment module**, offering **organic pesticide solutions** that are environmentally sustainable and aligned with modern agricultural practices.

The system is intended for use by **farmers**, **agronomists**, and other agricultural stakeholders, enabling them to quickly diagnose plant diseases and receive tailored treatment suggestions. Moving forward, the project can be **expanded** to support additional **plant species**, **diseases**, and more advanced **recommendation logic** to further enhance its utility in real-world farming contexts.

### **1.5 Organization of the Report**

This report is organized to provide a thorough examination of the project, from background research to the final results. Each section is designed to guide the reader through the different stages of the development and evaluation of the plant disease detection system. The content is structured as follows:

* **Literature Review**: This section provides an in-depth review of existing research and methodologies in the field of plant disease detection using deep learning. It highlights the advancements made in this domain, as well as the gaps and limitations that the current project aims to address. By understanding previous work, we establish the context for our own approach and the contributions of the project.
* **Methodology**: In this section, we describe the approach taken to develop the fusion-based deep learning model. We discuss the selection of datasets, the architecture of the model, and the integration of the pesticide recommendation system. This section lays out the theoretical and practical steps involved in designing the solution.
* **System Design**: Here, we outline the design of the entire system, detailing both the backend model (which handles plant disease detection) and the front-end user interface (which enables user interaction through a web application). The section focuses on how the two components interact and the overall user experience.
* **Implementation**: The implementation chapter covers the practical steps involved in building and deploying the model. We provide details on data preprocessing, model training, and the integration of additional features such as pesticide recommendations. This section also highlights any challenges encountered during the development process.
* **Results**: This section presents the performance metrics of the model, including accuracy, precision, recall, and other relevant evaluation measures. We also describe the testing process, including cross-validation and dataset-specific testing, and present the results obtained from the model in different scenarios.
* **Conclusion**: The report concludes with a summary of the key findings from the project. We also discuss the limitations of the current model and suggest potential areas for future work, including ways to improve the system’s accuracy, scalability, and real-world applicability.

This structured approach ensures that each aspect of the project is thoroughly explored and clearly communicated, providing a complete understanding of the work conducted and its potential impact in the field of plant disease detection.

### **2.** Literature Survey

In the early phases of plant disease detection, conventional machine learning (ML) models such as **Decision Trees**, **Support Vector Machines (SVMs)**, and **Random Forests** were widely employed. These models relied heavily on **handcrafted features** like color, shape, and texture to distinguish between healthy and diseased plants. While effective to an extent, these traditional approaches often struggled to **scale to larger, more diverse datasets** and lacked robustness in varying **lighting conditions, backgrounds**, and **crop species** [6].

With the rise of **deep learning**, particularly **Convolutional Neural Networks (CNNs)**, the paradigm shifted dramatically. CNNs enabled **automatic feature extraction** directly from raw images, eliminating the need for manual feature engineering. A seminal study by **Mohanty et al. [1]** demonstrated the potential of CNNs in plant disease detection using a large, curated dataset. Similarly, **Ferentinos [2]** trained deep neural networks on a dataset of **87,848 images**, achieving high classification accuracy across multiple plant species and disease categories.

The adoption of **transfer learning** further boosted performance in agricultural domains. Pre-trained models such as **VGG**, **ResNet**, and **InceptionNet** proved particularly effective when fine-tuned on smaller, domain-specific datasets [5], reducing training time and computational requirements while maintaining strong predictive capabilities.

To optimize both **accuracy and efficiency**, **Tan and Le [3]** introduced **EfficientNet**, a family of models that balances network depth, width, and input resolution. This model achieves superior performance with significantly fewer parameters and has since been adapted for agricultural applications with promising results.

Despite these advancements, single-model architectures often face limitations in terms of **generalization** and **robustness**. To address these issues, recent research has explored **fusion-based models**, which combine outputs or features from multiple CNNs to enhance performance. For instance, **Bucicov and Zaharescu [9]** reviewed various fusion strategies in plant pathology, highlighting their ability to generalize across diverse image domains. Likewise, **Molina et al. [10]** proposed a hybrid deep learning and ensemble approach, enhancing classification robustness under real-world conditions.

Standardized datasets like **PlantVillage [4]** have played a vital role in benchmarking models and promoting reproducible research. However, as **Choi et al. [7]** noted, most datasets are captured under controlled conditions, and there's an urgent need for more diverse and realistic datasets to ensure model reliability in practical, **uncontrolled environments**.

Importantly, while classification accuracy has improved significantly, there remains a **notable research gap** in integrating disease **diagnosis with actionable treatment recommendations**. Our research addresses this need by proposing a **fusion-based deep learning model** that not only achieves high accuracy in plant disease classification but also **recommends organic pesticides** as a sustainable treatment option. The fusion model integrates the strengths of three CNN architectures—Simple CNN, Deep CNN, and EfficientNetB0—capturing both **major and subtle features** to maximize diagnostic performance and support sustainable agriculture.

**2.1 Introduction to the Problem Domain Terminology:**  
 The identification of plant leaf diseases using advanced technologies involves several core concepts from computer vision and deep learning. The primary goal of plant disease detection is to identify symptoms that indicate the presence of infections or nutritional deficiencies in plant leaves.

* Feature extraction refers to the process of identifying significant visual patterns within images, such as color, texture, and edges, which help in distinguishing between healthy and diseased plant leaves. Traditionally, this process was performed manually by experts, but recent advancements in Convolutional Neural Networks (CNNs) have enabled the automatic learning of these features directly from raw image data.
* Transfer learning plays a crucial role in enhancing model performance by reusing pre-trained weights from models that have already been trained on large, diverse datasets. This technique allows the model to leverage knowledge learned from one task and apply it to a new, related task, significantly reducing the training time and improving accuracy.
* Model fusion involves combining multiple deep learning models to improve prediction accuracy and generalization. By leveraging different models’ strengths, fusion techniques can handle various features and patterns in data, leading to more robust and reliable predictions.

Together, these methods contribute to a reduction in manual errors, accelerate disease detection processes, and promote more sustainable agricultural practices by providing faster, more accurate diagnosis and treatment recommendations.

### **2.2 Existing Solutions:**

### **2.2.1 Traditional Machine Learning Models:**

In the early stages of **plant disease detection**, traditional machine learning models played a crucial role in laying the foundation for more advanced systems. These models utilized well-established algorithms such as **Decision Trees**, **Support Vector Machines (SVMs)**, and **Random Forests** to classify plant diseases based on **manually extracted features** from images.

#### **Manually Extracted Features:**

Traditional machine learning models relied on manually crafted features from input images to perform disease classification. Some of the commonly used features included:

* **Color Histograms:** Used to capture the distribution of colors in the plant images, which can reveal signs of disease, such as discoloration or changes in leaf pigmentation.
* **Edge Detection:** Techniques like the **Canny edge detector** were applied to highlight boundaries or transitions in the image, which are important for identifying leaf damage or the structure of the plant.
* **Texture Descriptors:** Features such as **Haralick textures** were used to capture the textural patterns in the image, which could differentiate between healthy and diseased plant tissues.

#### **Advantages of Traditional Models:**

1. **Simplicity:** These models were relatively simple to implement and computationally less expensive compared to deep learning approaches.
2. **Interpretability:** Machine learning models like Decision Trees are easy to interpret, providing insights into how predictions were made based on the extracted features.
3. **Low Resource Requirements:** Traditional models did not require high-end hardware or large amounts of training data, making them suitable for environments with limited resources.

#### **Limitations of Traditional Models:**

Despite their initial success, these traditional machine learning models had several notable drawbacks:

1. **Limited Scalability:**
   * Traditional machine learning models struggled to scale effectively as datasets grew in size and complexity. As more plant species, disease types, and variations in environmental conditions were considered, the handcrafted features became insufficient for accurate classification.
   * Handling larger datasets with a greater variety of plant species required complex feature engineering, which was both time-consuming and prone to human error.
2. **Poor Generalization to Real-World Conditions:**
   * These models were trained on a fixed set of features, which meant they were highly sensitive to the quality of the images and the conditions under which they were captured.
   * Real-world conditions often presented challenges such as:
     + **Varying lighting:** Images taken in different lighting conditions can cause variations in color and texture that traditional models were not robust enough to handle.
     + **Background Clutter:** Complex or busy backgrounds could confuse the feature extraction process, making it difficult for the models to focus on relevant plant structures.
     + **Different Camera Quality:** Images taken with different cameras or under different resolutions led to inconsistent feature extraction, reducing the model's performance on new data.
3. **Feature Engineering Bottleneck:**
   * The process of manually extracting features required domain expertise and was inherently limited by the features that could be captured. As a result, this approach struggled to capture the complex and subtle patterns in plant images that may be critical for accurate disease detection.
   * These models were also unable to adapt to new plant species or diseases without significant manual intervention in feature extraction and model retraining.

#### **Shift to Deep Learning:**

Due to these limitations, researchers eventually turned to **deep learning** techniques, particularly **Convolutional Neural Networks (CNNs)**, to overcome the challenges of traditional machine learning approaches. Unlike traditional models that required manual feature extraction, deep learning models learn features directly from the raw image data, making them more adaptable, scalable, and accurate, especially in large and complex datasets.

In conclusion, while traditional machine learning models provided a solid starting point for plant disease detection, their reliance on handcrafted features and their inability to generalize effectively to diverse and dynamic real-world conditions limited their usefulness. As the need for more scalable, accurate, and robust systems grew, deep learning models emerged as the superior choice, enabling more effective plant disease detection even under complex and varied conditions.

**2.2.2 CNN-Based Image Classification**:  
The introduction of Convolutional Neural Networks (CNNs) marked a transformative shift in plant disease classification. Unlike traditional models, CNNs are capable of performing automatic feature extraction, allowing them to learn relevant patterns directly from raw image data. This eliminates the need for manual feature engineering and enables the model to adapt to a broader range of plant species and environmental conditions.

One landmark study by Mohanty et al. demonstrated the power of CNNs in accurately detecting plant diseases. Using a large-scale dataset, the authors showed that CNNs could achieve high classification accuracy without relying on handcrafted features. The network was able to learn both spatial and contextual information from the images, making it particularly robust for plant disease detection. This capability of capturing intricate patterns in image data has made CNNs the go-to method for modern plant disease detection systems, providing a more reliable and scalable solution compared to traditional machine learning techniques.

### **2.2.3 Transfer Learning with Pretrained Models**

Transfer learning has revolutionized the field of image classification, particularly in domains like plant disease detection where obtaining large volumes of labeled data is often challenging. Instead of training deep learning models from scratch—which typically requires extensive data and computational resources—transfer learning leverages knowledge from models that have already been trained on large-scale datasets such as **ImageNet**, which contains over 1.2 million images across 1,000 object categories.

In the context of this study, transfer learning plays a pivotal role in enhancing the performance and generalization capabilities of the plant disease detection system. Researchers like **Ferentinos (2018)** have demonstrated the effectiveness of using pretrained architectures such as **VGG16**, **ResNet50**, and **InceptionNet** for plant disease classification. These networks have been shown to learn highly transferable visual features—from basic edges and textures in early layers to more complex patterns and structures in deeper layers—that are useful for a wide range of tasks, including the identification of subtle symptoms in plant leaves.

By fine-tuning these pretrained models on domain-specific datasets like **PlantVillage**, **Plant Leaves**, and **PlantDoc**, the system can adapt the generic feature representations to the nuances of plant pathology. This results in:

* **Improved Accuracy**: The model benefits from a strong feature extraction backbone, leading to superior classification performance even on limited data.
* **Faster Convergence**: Since the model starts with weights that are already optimized for image recognition, fewer training epochs are needed to reach optimal performance.
* **Reduced Overfitting**: The pretrained layers provide robust initial representations that generalize well, especially when working with small or noisy agricultural datasets.
* **Lower Computational Cost**: Transfer learning reduces the need for massive GPU resources, making it accessible for real-world deployment in resource-constrained environments.

In this project, **EfficientNetB0**, a lightweight and high-performing CNN architecture pretrained on ImageNet, was used as one of the base models. Its balanced design of width, depth, and resolution, combined with pretrained weights, significantly contributed to the overall accuracy and efficiency of the fusion-based system.

Overall, the incorporation of transfer learning not only improved the scalability of the model to new crops and diseases but also laid the groundwork for developing intelligent agricultural tools that can be quickly adapted to diverse environments with minimal re-training.

### **2.2.4 EfficientNet for Resource-Efficient Accuracy**

The introduction of **EfficientNet** by **Tan and Le (2019)** marked a significant milestone in the development of deep learning architectures. EfficientNet employs a novel compound scaling method to balance the three key dimensions of a neural network: **width**, **depth**, and **input resolution**. Traditional approaches to scaling these dimensions often led to models that were either too deep (increasing computational complexity) or too wide (leading to inefficient use of parameters). EfficientNet, however, systematically scales these factors in a balanced manner, resulting in a series of models that achieve impressive classification performance while significantly reducing the number of parameters and computational load.

What sets EfficientNet apart from other architectures is its **compound scaling** approach, which ensures that the model’s performance improves in proportion to the resources available. Rather than arbitrarily increasing one dimension (e.g., depth) while neglecting others, EfficientNet scales all three factors simultaneously in an optimal manner, leading to a more efficient and effective architecture. This results in:

* **Higher Accuracy**: EfficientNet achieves state-of-the-art performance on benchmark datasets with fewer parameters compared to traditional models like ResNet and VGG.
* **Fewer Parameters**: By scaling the model efficiently, EfficientNet drastically reduces the number of parameters, making it far more lightweight.
* **Lower Computational Requirements**: The reduced model size translates into lower computational costs and faster inference times, making it ideal for deployment on resource-constrained devices.

For applications in fields like agriculture, where high-end hardware may not be accessible or practical, **EfficientNet** provides a viable solution. Its lightweight nature allows for **resource-efficient inference**, making it well-suited for **field-based applications** like plant disease detection. For example, small-scale embedded devices, such as smartphones, Raspberry Pi, or drones, can run EfficientNet models without the need for powerful GPUs or cloud-based resources. This is especially important for farmers in remote areas, where access to high-performance computing infrastructure may be limited.

In agricultural research, EfficientNet has been successfully applied to plant disease detection tasks, with studies demonstrating its ability to perform effectively even on smaller, domain-specific datasets like those used for identifying plant diseases. By deploying **EfficientNet-based models**, researchers and developers have been able to create systems that are not only accurate but also lightweight and capable of operating in real-time, even in low-resource environments.

For instance, in the context of plant disease detection, EfficientNet provides a powerful solution that helps farmers identify diseases quickly and accurately using **low-cost mobile devices**. This reduces the need for heavy, expensive hardware, thus improving the **scalability and accessibility** of agricultural diagnostic tools.

Ultimately, EfficientNet serves as a prime example of how modern deep learning architectures can be tailored for resource-efficient applications, opening the door for **sustainable and scalable plant health monitoring systems**.

**2.2.5 Fusion-Based and Hybrid Architectures :**

To address the limitations associated with single-model approaches in plant disease detection, fusion-based models have gained significant traction in recent years. These models combine the outputs of multiple individual models to exploit their complementary strengths, thereby enhancing performance across diverse datasets and environmental conditions. Single-model architectures, while effective in controlled environments, often struggle with generalizing to real-world complexities such as variations in lighting, background clutter, and differences in plant species or diseases. Fusion models mitigate these issues by leveraging multiple perspectives on the data, which improves generalization and robustness.

Advantages of Fusion-Based Models: Improved Generalization: By combining the predictions of several models, fusion-based systems can generalize better to new, unseen data, making them more resilient to the inherent variability in agricultural datasets.

Increased Robustness: The fusion of models, especially those with complementary strengths, leads to more consistent predictions even under challenging conditions like fluctuating lighting or background noise.

Error Reduction: By aggregating the outputs of multiple models, fusion strategies can reduce errors introduced by individual models, resulting in higher accuracy and more reliable predictions.

In the field of plant disease detection, these models can outperform single-model systems, as they can aggregate different feature extraction capabilities and prediction strategies into a unified decision-making process.

Hybrid Architectures in Plant Disease Detection: One of the most notable advancements in this area is the development of hybrid models, which combine different types of models to exploit their distinct strengths. Molina et al. (2020) proposed a hybrid architecture that integrates Convolutional Neural Networks (CNNs) with ensemble learning techniques. This approach has proven highly effective in plant disease detection, as it combines CNNs' ability to extract intricate features from images with the power of ensemble methods, which aggregate the predictions of multiple models to improve overall accuracy and robustness.

How Hybrid Models Work: Feature Extraction (CNNs): CNNs are well-suited for automatically learning hierarchical features from raw image data. In the context of plant disease detection, CNNs can capture fine-grained texture, color, and structural patterns that are indicative of plant health and disease.

Ensemble Learning (e.g., Random Forest, Gradient Boosting): After feature extraction, ensemble learning techniques combine predictions from multiple models to increase the accuracy of the final output. For instance, a model like Random Forest aggregates predictions from a collection of decision trees, each trained on different subsets of the data, leading to more robust and reliable outcomes.

The hybrid fusion approach enables the system to:

* Capture both low-level and high-level features from images.
* Combine the decision-making power of different models to mitigate the risk of overfitting or underfitting, which can occur when relying on a single model type.
* Produce resilient predictions in complex, real-world agricultural settings where factors such as changing environmental conditions, diverse plant species, and varying disease symptoms may affect performance.

Real-World Applications and Performance: Hybrid and fusion-based architectures have demonstrated improved performance, particularly in real-world agricultural scenarios where challenges like varying lighting, backgrounds, and plant species diversity are common. For example:

In agricultural fields, lighting conditions change throughout the day, and plant leaves may be partially obstructed by other objects or environmental factors. A fusion-based model can account for such variability, ensuring that predictions remain accurate even in less-than-ideal conditions.

Different plant species exhibit varied responses to disease, and the symptoms may differ widely across species. A hybrid model can generalize across multiple species, improving detection rates in mixed-species environments.

Benefits in Plant Disease Detection: Higher Accuracy: The combination of models allows the system to learn more complex and diverse patterns in plant images, leading to higher accuracy compared to single-model systems.

Improved Robustness: Fusion models are better equipped to handle real-world challenges such as noisy images, inconsistent lighting, and background clutter.

Scalability: Fusion-based approaches can easily be extended to handle new plant species or diseases by simply adding additional models or modifying the ensemble learning techniques.

**2.3 Related Works:**

In recent years, significant attention has been dedicated to improving the generalization of plant disease detection models and addressing the challenges posed by real-world variability in plant imagery. While widely used datasets like PlantVillage have facilitated the benchmarking of models, they often contain images captured under controlled conditions, which do not fully represent the diversity encountered in real agricultural settings. Choi et al. emphasized the importance of incorporating more diverse and realistic datasets, such as the PlantDoc dataset, which includes plant images captured in varying environmental conditions. This shift towards more real-world datasets is crucial for building models that can generalize well to a wider array of plant species, diseases, and environmental factors.

Despite advancements in improving classification accuracy through CNNs and other deep learning techniques, most existing systems focus primarily on disease detection and classification, with little to no integration of actionable solutions for treatment or prevention. Few systems provide holistic solutions that bridge the gap between diagnosis and practical, sustainable agricultural advice.

Our work addresses this gap by combining disease classification with organic pesticide recommendations, thus offering a more complete and sustainable solution. This integration not only helps identify diseases more accurately but also provides eco-friendly treatment suggestions, enhancing the overall utility of the system for farmers and agronomists seeking practical guidance in disease management.

**2.4 Tools and Technologies Used:**

This section outlines the key tools and technologies utilized in the development and testing of the plant disease detection and pesticide recommendation system.

**2.4.1 Google Colaboratory (Colab)** :

Google Colab served as the primary development environment throughout the project. Colab is a cloud-based platform that provides free access to high-performance GPUs and TPUs, which significantly accelerated the training and evaluation of deep learning models. By leveraging these resources, the development process was streamlined, eliminating the need for local computational hardware. Additionally, Colab supports real-time code collaboration, making it an ideal tool for team-based research and rapid prototyping. The interactive nature of Colab also facilitated easier debugging and model iteration.

**2.4.2 Machine Learning** :

During the initial phase of the project, **traditional machine learning algorithms** were investigated for plant disease classification using manually engineered features. Models such as:

* **Support Vector Machines (SVM)**
* **Decision Trees**
* **Random Forests**

were employed on datasets where features like **color histograms**, **texture descriptors** (e.g., Local Binary Patterns), and **edge-based features** were extracted through conventional image processing techniques.

These methods offered valuable insights into the importance of specific visual patterns in disease detection and served as a **baseline for performance benchmarking**. However, their limitations became apparent as the complexity and variability of input images increased. Specifically, they struggled with:

* High intra-class variability (e.g., different symptoms for the same disease)
* Sensitivity to background clutter and lighting conditions
* Lack of end-to-end learning capabilities

To address these issues, the project transitioned to **deep learning-based models**, which automatically learn relevant features directly from the data, offering superior performance, scalability, and generalization on real-world plant disease datasets.

**2.4.3 Deep Learning** :

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), became central to this research due to their ability to automatically extract features and recognize multi-level patterns directly from raw plant leaf images. The CNN architecture used in this project combined standard layers with custom-designed components, enhancing both the accuracy and generalization of the model. By using deep learning, the system could efficiently handle large-scale image data and provide real-time disease classification with improved precision compared to traditional methods.

**2.4.4 TensorFlow** :

**TensorFlow** was the primary framework utilized for building, training, and deploying the CNN-based and fusion models. As an open-source, high-performance deep learning library, TensorFlow provided the necessary tools to develop and scale complex neural networks efficiently. Its high-level API, **Keras**, enabled rapid prototyping and experimentation with multiple model architectures.

TensorFlow’s **support for both CPU and GPU** computation allowed for efficient training of resource-intensive models, while its robust deployment capabilities ensured a smooth transition from development to real-world application. This facilitated **seamless integration** of the final model into the web-based interface, supporting real-time disease prediction and pesticide recommendation.

## **3. DESIGN OF PROPOSED SYSTEM / METHOD / ALGORITHM**

### **3.1 Block Diagram**

The proposed plant leaf disease detection and pesticide recommendation system follows a modular architecture with clear steps for processing and classifying plant leaf images. The system is composed of several key blocks, each performing a specific task in the pipeline, as shown below:

#### **1. Input Image**

The process begins with the user uploading a **plant leaf image** through the web interface. This image serves as the input to the entire system.

#### **2. Preprocessing**

Before feeding the image into the deep learning models, the system performs necessary **preprocessing** to ensure the image is in the correct format for analysis. This involves:

* **Resizing** the image to a consistent size that aligns with the model input specifications.
* **Normalization** of pixel values to a range suitable for neural network processing (typically between 0 and 1 or -1 and 1), ensuring the model receives properly scaled data for better convergence during training.

#### **3. Parallel Feature Extraction**

The next step involves **parallel feature extraction** from the input image using three distinct models, each trained to capture different levels of abstraction from the image.

* **Simple CNN**: A shallow CNN designed to extract basic spatial features, such as edges and simple textures, which can help identify obvious disease markers in the image.
* **Deep CNN**: A deeper CNN that captures more complex patterns and hierarchical features. It is capable of identifying advanced symptoms of diseases, often by processing more abstract representations of the image.
* **EfficientNetB0**: A **pre-trained model** using **transfer learning** to leverage features from a model trained on a large, general-purpose dataset (like ImageNet). This model extracts **multi-scale** features and can recognize both global and local patterns in the plant leaf image.

#### **4. Feature Fusion**

The system combines the **extracted features** from all three models into a single, comprehensive vector. This process of **feature fusion** consolidates the strengths of each model’s representation into one unified set of features. The fusion step is crucial because it allows the model to learn from a diverse set of features, leading to a more robust disease classification.

#### **5. Fully Connected Layer**

Once the features are fused, they pass through a **fully connected (dense) layer**. This layer helps in **mapping the combined feature vector** to the final output by performing further transformations. The dense layers help the model in making more refined predictions and improving its performance by capturing the relationships between the features.

#### **6. Classification Output**

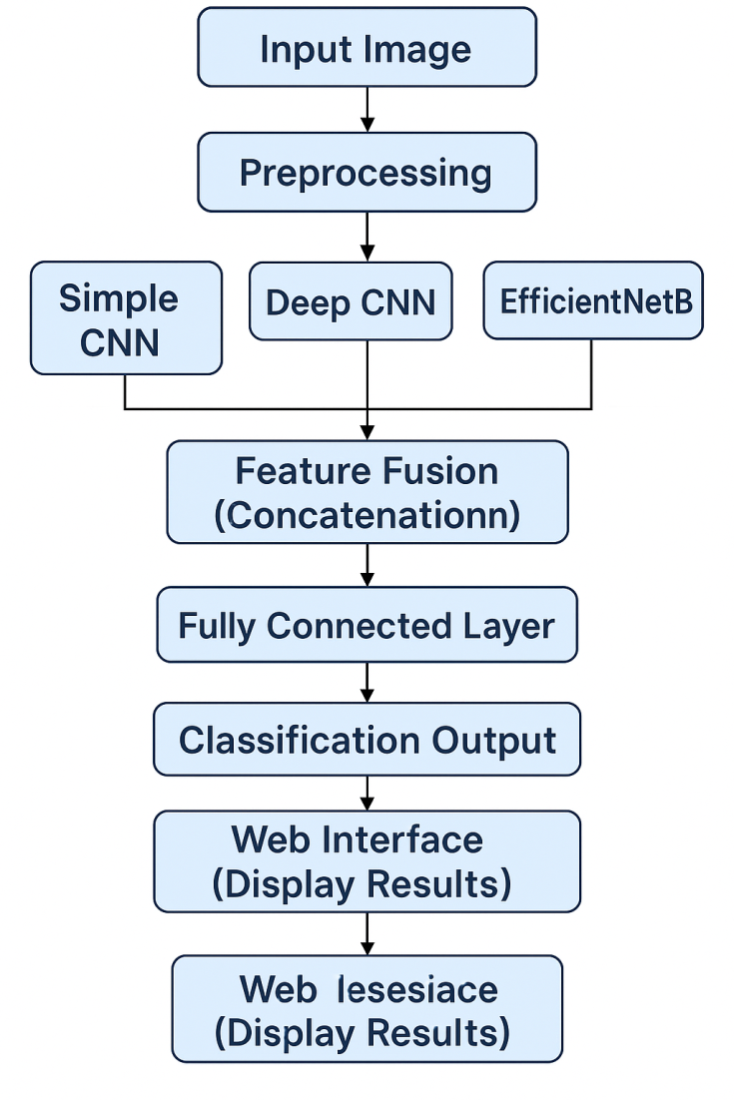
The final layer of the system produces the **classification output**. Here, the model predicts the **disease class** of the input plant leaf image based on the learned features. The output is typically a set of class probabilities (e.g., the probability of the image belonging to each disease class).

#### **7. Pesticide Recommendation Module**

After determining the disease, the system links the identified disease to an **organic pesticide recommendation**. The system fetches the corresponding pesticide suggestion from a **mapped database** of eco-friendly solutions that are appropriate for the disease identified.

#### **8. Web Interface**

The system’s user-friendly **web interface** provides the final layer of interaction for users. The interface allows users to easily upload plant leaf images, and it displays the disease classification results and pesticide recommendations in real-time. This design ensures that the system is easily accessible and can be utilized by farmers, agronomists, and other agricultural stakeholders.



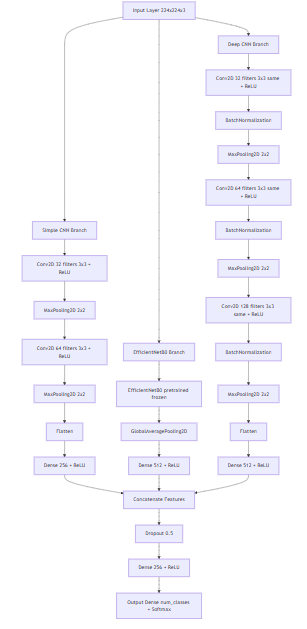
**Block Diagram**

### **3.2 Flowchart / Activity Diagram**

#### **System Flow**

The activity flow of the system can be visualized in the following steps:

1. **User Uploads Image:**
   * The process begins when the user accesses the web application and **uploads a plant leaf image**.
   * The image can be uploaded through a simple interface, allowing ease of use for farmers or agricultural workers.
2. **Image Preprocessing:**
   * Once the image is uploaded, it goes through a preprocessing stage where:
     + The image is **resized** to fit the input dimensions required by the model.
     + The pixel values are **normalized** (scaled to a standard range) to optimize model input and ensure better performance during processing.
3. **Parallel Feature Extraction:**
   * After preprocessing, the image is sent to **three parallel convolutional neural network branches**:
     + **Simple CNN**: Extracts basic spatial features (edges, shapes).
     + **Deep CNN**: Extracts more complex, high-level features (patterns, textures).
     + **EfficientNetB0**: A pre-trained model (via transfer learning), extracting multi-scale features using its efficient architecture.
4. **Feature Fusion:**
   * The features extracted from the three branches (Simple CNN, Deep CNN, and EfficientNetB0) are **concatenated** into a single vector.
   * This fusion step combines the strengths of all three models, resulting in a richer, more comprehensive feature representation of the input image.
5. **Fully Connected Layers:**
   * The concatenated feature vector is then passed through **fully connected (dense) layers**.
   * These layers perform further processing to refine the features and make predictions. The dense layers are crucial for improving the model's ability to classify the disease accurately.
6. **Prediction & Pesticide Recommendation:**
   * The final output from the dense layers is the **predicted disease class**.
   * Based on the predicted disease, the system retrieves an **organic pesticide recommendation** from a mapped database. This is an eco-friendly solution to treat the detected disease.
7. **Display Results to User:**
   * Finally, the **prediction results** (disease identification) and **pesticide recommendation** are displayed on the web application frontend.
   * The user receives the disease classification and suggested treatment in a user-friendly format, enabling them to take timely action.



Model Architecture

**3.3 Theoretical Foundation / Algorithms:**

The proposed system leverages a combination of deep learning models and decision logic to perform plant disease classification and provide relevant pesticide recommendations. The core theoretical components are outlined below:

* Convolutional Neural Networks (CNNs): CNNs are a class of deep neural networks particularly effective for image processing tasks. They work by applying convolution operations that automatically learn spatial hierarchies of features through layers. Key components of CNNs include:
* Convolutional Layers: Detect local patterns such as edges, textures, and shapes.
* Pooling Layers: Downsample the feature maps to reduce dimensionality and computational load.
* Fully Connected Layers: Interpret the extracted features for final classification.

CNNs are used in both the simple and deep custom branches of the proposed architecture to extract spatial features from leaf images.

**EfficientNetB0:**

EfficientNetB0 is a pre-trained CNN architecture known for its high accuracy and computational efficiency. It uses a compound scaling method to uniformly scale network width, depth, and resolution using a set of fixed scaling coefficients. Its benefits include:

* Fewer parameters compared to older architectures like VGG or ResNet.
* Faster inference suitable for real-time applications.
* Strong feature extraction capabilities due to pretraining on large datasets like ImageNet.

EfficientNetB0 serves as a third feature extractor in the proposed parallel architecture.

### **Feature Fusion: A Comprehensive Explanation**

Feature fusion is a powerful strategy that enhances the performance of machine learning models, particularly in deep learning tasks such as plant disease detection. By integrating multiple feature representations from various models, the system leverages the strengths of each individual model to create a more robust and accurate classification framework. In this project, the fusion of three distinct Convolutional Neural Networks (CNNs)—**Simple CNN**, **Deep CNN**, and **EfficientNetB0**—forms the cornerstone of the model architecture, providing a unified, enriched feature vector that improves both the classification accuracy and generalization of the system.

### 1. **Complementary Feature Capture:**

Each CNN architecture in the system is specialized to capture different levels of abstraction from the input images. By combining these features, the system benefits from a broad and comprehensive representation of the data, ensuring that various patterns and nuances within the images are captured.

* **Simple CNN**:
  + This model focuses on extracting low-level features, such as **edges**, **textures**, and **simple patterns**. These features are essential for identifying basic structures in images, such as the boundaries of leaves, veins, or other plant structures. Simple CNN is particularly useful in capturing the fundamental components that make up plant images.
* **Deep CNN**:
  + Deep CNNs are capable of capturing more **complex** and **abstract features**. These might include parts of plants, such as the shape of leaves or the arrangement of branches. As the network deepens, it learns hierarchical representations that build upon the low-level features from earlier layers, providing insights into mid-level patterns like shapes, contours, and textures that are essential for distinguishing diseases.
* **EfficientNetB0**:
  + EfficientNetB0 is designed to capture **high-level semantic features**. These features include more context-driven patterns, such as **object recognition** (e.g., recognizing the presence of specific plant parts or diseases) and broader **contextual relationships** between various elements in the image. EfficientNetB0’s compound scaling approach allows it to maintain a balance between accuracy and efficiency, making it effective in capturing these high-level patterns while being computationally efficient.

#### Fusion Benefit:

By combining the low, mid, and high-level features from the three models, the system gains a **richer feature set**, enabling it to better understand and classify complex patterns in plant disease images. This fusion allows the model to capture **complementary** information from all levels, improving overall performance. For example, while a Simple CNN might detect edges in a plant image, EfficientNetB0 might understand whether those edges belong to a diseased or healthy part of the plant, providing a more accurate classification.

### 2. **Improved Generalization:**

One of the most significant challenges in plant disease detection is the variability of data. Real-world images can vary dramatically due to factors like **lighting**, **background noise**, **image resolution**, and **plant species**. A single CNN architecture may struggle to generalize well across such diverse conditions, leading to poor performance when deployed in the field.

#### Fusion Benefit:

By integrating features from multiple CNNs, the system becomes **more resilient** to these variations. Since each model captures different features of the images, the fusion of these features provides a more holistic view of the input data. This enables the model to perform well not only on clean, controlled datasets but also on real-world data that may exhibit more noise, distortions, or environmental inconsistencies. The **diverse feature set** allows the model to generalize better, ensuring that it performs consistently across different conditions.

In essence, the fusion of multiple models with complementary capabilities helps the system **adapt to a wide range of scenarios**, making it more effective when deployed in the field where environmental factors and image quality can vary.

### 3. **Reduction in Overfitting:**

Overfitting occurs when a model becomes too tailored to the training data, effectively memorizing patterns rather than learning generalizable features. This is especially problematic in machine learning models, where the system may perform exceptionally well on the training dataset but fail to generalize to unseen data.

#### Fusion Benefit:

By leveraging multiple CNN architectures, the risk of overfitting is significantly reduced. Each model captures different aspects of the data and learns from different perspectives. As a result, the **fused feature vector** is less likely to be biased toward the training data, since it represents a combination of learned patterns from various models. The diversity in features reduces the chances of the model memorizing the training data and improves its ability to generalize to new, unseen plant images.

Furthermore, this fusion technique helps ensure that the model is **robust to variations** in the data, as it is not dependent on any single model’s learned biases. This results in a more **resilient** system that performs better on both the training and testing datasets.

### 4. **Ensemble Learning Effect:**

The process of feature fusion effectively combines the strengths of multiple individual models, leading to an ensemble-like effect. In ensemble learning, multiple models contribute to the final prediction, often resulting in better performance than any single model could achieve on its own.

#### Fusion Benefit:

By **combining predictions** from different CNN models, the system can capitalize on the **complementary strengths** of each model. This approach minimizes the **weaknesses** of individual models and ensures that the final prediction benefits from a more diverse range of learned features. The ensemble approach thus improves the **accuracy** and **robustness** of the system’s disease classification capabilities.

### **Classification Layer**

After **feature fusion**, the resulting concatenated feature vector is passed through a **fully connected (dense) neural network** that performs the final classification. This stage is responsible for interpreting the combined features and mapping them to the appropriate plant disease class.

The classification pipeline consists of:

* **Dense Intermediate Layers:**  
  One or more fully connected layers equipped with **ReLU (Rectified Linear Unit)** activation functions introduce non-linearity and enable the network to learn complex decision boundaries.
* **Output Layer with Softmax Activation:**  
  The final layer uses a **Softmax activation function** to produce a probability distribution across all target plant disease classes. This ensures that the model not only makes a prediction but also provides a confidence score for each class.
* **Prediction Decision:**  
  The disease class corresponding to the **highest probability** in the Softmax output is selected as the final prediction.

**Recommendation Logic:**

Once a plant disease is predicted, the system uses rule-based logic to retrieve a relevant organic pesticide recommendation. This is done via:

* A dictionary or lookup table where each disease class is mapped to an eco-friendly pesticide.
* This mapping provides actionable insight alongside the diagnosis, aiding users in sustainable disease management.

## **4. IMPLEMENTATION OF THE PROPOSED SYSTEM**

### **4.1 Module Description**

The proposed system is modular in design, enabling seamless integration of classification and recommendation tasks. The key modules include:

* **Image Upload Module**  
  Facilitates the uploading of plant leaf images through a user-friendly web interface. This is the entry point for user interaction with the system.
* **Preprocessing Module**  
  Processes the uploaded image by resizing it to a fixed input dimension and normalizing pixel values. This ensures consistency and compatibility with the input requirements of all models.
* **Model Inference Module**  
  Executes three parallel neural networks—Simple CNN, Deep CNN, and EfficientNetB0—on the preprocessed image. Each model extracts features at varying levels of abstraction.
* **Fusion Module**  
  Combines the features extracted from all three models using concatenation. The resulting feature vector provides a richer representation for classification.
* **Prediction Module**  
  Feeds the fused feature vector into a dense network that outputs the predicted disease label using softmax activation.
* **Pesticide Recommendation Module**  
  Maps the predicted disease to an organic pesticide using a predefined dictionary. This module provides actionable guidance for disease treatment.
* **Frontend Display Module**  
  Displays the classification result and the recommended organic pesticide in a clear, interpretable format to the user via the web interface.

### **4.2 Algorithms**

### **Convolutional Neural Network (CNN) Algorithm**

* Applies convolution operations to learn local patterns (e.g., edges, textures).
* Uses **ReLU activation** to introduce non-linearity.
* **Max pooling** layers reduce spatial dimensions and computational load.
* The final **fully connected layers** interpret the features to produce an output vector for classification.

#### **EfficientNetB0 (Pretrained Model)**

* Utilizes **compound scaling** to uniformly scale depth, width, and resolution for better performance-efficiency tradeoff.
* Used here as a **feature extractor**, omitting the original classification layers.
* Pretrained on **ImageNet**, enabling effective transfer learning.

#### **Feature Fusion**

* Concatenates feature vectors from the three parallel models:  
  Fused\_Vector = [Simple\_CNN\_Features | Deep\_CNN\_Features | EfficientNetB0\_Features]
* The fused vector is passed into a **dense classifier** with softmax output to determine the most probable disease class.

#### **Pesticide Recommendation**

* A disease-to-organic-pesticide dictionary is used.
* The predicted class is used as a key to fetch the recommended pesticide.

**4.3 Dataset Description :**

To ensure robustness and real-world applicability, the system was trained and evaluated using three publicly available plant disease datasets:

* PlantVillage Dataset
  + Contains approximately 54,000 high-resolution leaf images.
  + Covers 38 plant classes with various disease types.
  + Captured under controlled conditions with clean backgrounds and consistent lighting.
  + Used primarily for initial training and benchmarking model performance.
* Plant Leaves Dataset
  + Comprises images of plant leaves captured in natural environments with varying lighting and background conditions.
  + Enhances the model’s generalization ability and robustness against real-world variability.
* PlantDoc Dataset
  + Features images taken in real-world farming scenarios, often containing noise, clutter, and variable camera angles.
  + Serves as a benchmark for testing generalization to field conditions.
  + Useful for simulating real deployment environments.

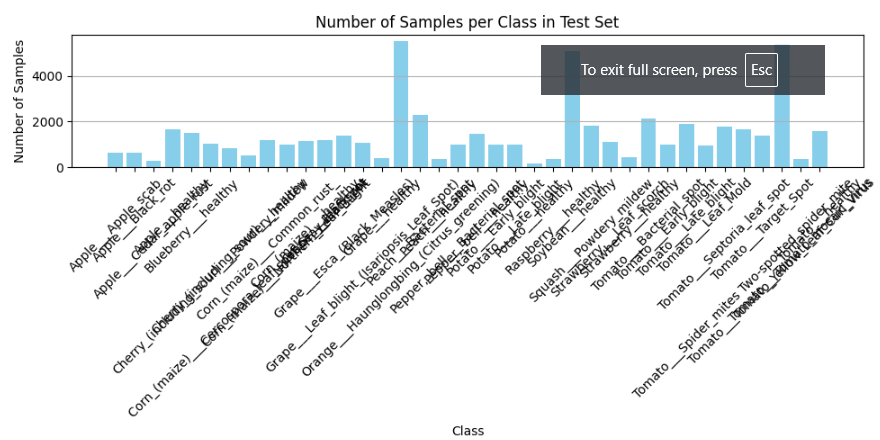
 

Dataset samples

**4.4 Testing Process**

To ensure the model’s reliability, accuracy, and ability to generalize across varying conditions, a comprehensive multi-phase testing methodology was implemented:

* Train-Test Split
  + All three datasets—PlantVillage, Plant Leaves, and PlantDoc—were individually divided using an 80:20 train-test ratio.
  + This ensured that the test data remained unseen during training, providing a fair and unbiased evaluation of model performance.
* Cross-Validation
  + A K-Fold Cross-Validation strategy (typically K=5) was applied during training, allowing the model to be evaluated across multiple subsets.
  + This helped reduce overfitting and ensured the model’s performance was consistent and robust across different data partitions.
* Evaluation Metrics:
  + The model was assessed using standard classification metrics to obtain a comprehensive understanding of its performance:
  + Accuracy: Proportion of total correct predictions.
  + Precision: Proportion of true positive predictions among all predicted positives.
  + Recall (Sensitivity): Proportion of true positives identified out of all actual positives.
  + F1-Score: Harmonic mean of precision and recall, offering a balance between both metrics.
* Dataset-Specific Performance :
  + PlantVillage Dataset: Achieved >98% accuracy due to clean, high-resolution images and controlled backgrounds, indicating excellent model learning under ideal conditions.
  + Plant Leaves Dataset: Showed a moderate performance drop due to diverse lighting conditions and real-world backgrounds, demonstrating the model’s capacity to generalize with slight variability.
  + PlantDoc Dataset: Faced the most significant challenge, as the dataset includes cluttered environments, occlusions, and varied resolutions. While performance declined, the model still provided acceptable predictions, validating its baseline robustness.
* Web Interface Testing :
  + The end-to-end pipeline, including image upload, preprocessing, inference, and recommendation, was tested through the integrated web interface.
  + The frontend was evaluated for:
  + Responsiveness: Near real-time prediction speed.
  + Usability: Simple user experience suitable for non-technical users.
  + Accuracy of Output: Validated disease classification and pesticide recommendation accuracy.



* Test set data distribution

## **5. RESULTS / OUTPUTS AND DISCUSSIONS**

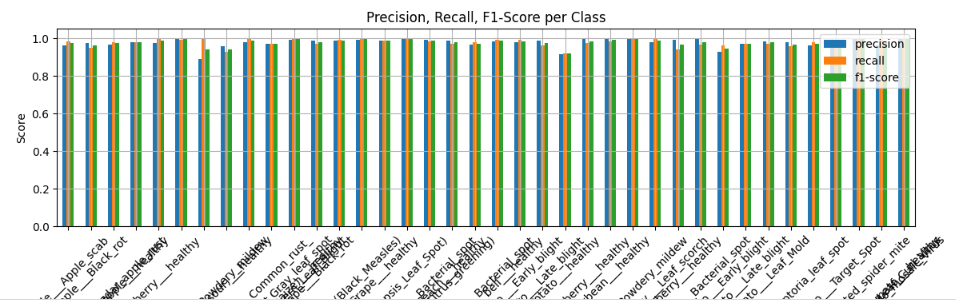
### **5.1 Results and Performance Metrics**

In this section, we present the performance of the proposed fusion model on three datasets: **PlantVillage**, **Plant Leaves**, and **PlantDoc**. The model’s performance was evaluated using standard classification metrics: **accuracy**, **precision**, **recall**, and **F1-score**. These metrics are crucial for assessing the effectiveness of the model in correctly classifying plant diseases and minimizing false predictions. The summary of the results is provided below:

* **Table 1. Fusion Model Performance on Plant Village Dataset**

|  |  |  |
| --- | --- | --- |
| Accuracy (%) | Precision (%) | Recall (%) |
| 98.32 | 98.29 | 98.277 |

* The model achieved excellent performance on the **Plant Village** dataset, with an accuracy of **98.32%**. This dataset, containing clean and high-quality images, allowed the model to perform optimally, yielding very high precision and recall.
* The accuracy dropped to **69.3%** on the **Plant Leaves** dataset, which includes images with diverse lighting conditions and environmental variations. This result suggests that the model’s performance is impacted by real-world complexities.
* The lowest performance was observed on the **PlantDoc** dataset, with an accuracy of **51.4%**. This dataset contains real-world images with noise, clutter, and varying environmental conditions, highlighting the challenges of deploying models in uncontrolled environments.



Precision, Recall , F1-Score per Class

### **5.2 Discussion**

The proposed fusion-based model exhibited strong classification performance, particularly on well-curated datasets. Key insights are as follows:

* High Accuracy on Controlled Data On the PlantVillage dataset, the model achieved over 98% accuracy, showcasing its effectiveness in identifying plant diseases under ideal conditions. The fusion of Simple CNN, Deep CNN, and EfficientNetB0 enabled the system to leverage diverse feature representations—ranging from low-level textures to high-level semantic structures—enhancing both accuracy and robustness.
* Performance on Real-World Data On more challenging datasets such as PlantDoc, which include noise, varied lighting, and inconsistent image quality, a noticeable drop in accuracy was observed. This outcome aligns with known challenges in deploying deep learning models in real-world environments, where domain shift and data variability significantly impact performance.
* Limitations and Future Improvements The observed performance gap highlights the need for:
  + Domain adaptation techniques to align training data with real-world scenarios.
  + Advanced data augmentation strategies (e.g., simulating lighting changes, noise) to improve generalization.
  + Potential integration of attention mechanisms or transformers to enhance spatial focus in noisy backgrounds.
* Practical Value Through Pesticide Recommendation A key innovation in this system is the pesticide recommendation module, which maps the predicted disease class to an organic pesticide suggestion.
  + This adds real-world utility, turning diagnosis into actionable guidance.
  + Especially beneficial for organic and sustainable farming, where chemical pesticide use is minimized.
  + Promotes eco-friendly plant disease management, making the system both intelligent and environmentally conscious.

## **6. CONCLUSIONS / RECOMMENDATIONS**

**6.1 Conclusions** :

This work presents a fusion-based deep learning system for plant leaf disease detection, enhanced with an organic pesticide recommendation module. The system combines the strengths of three distinct CNN architectures—Simple CNN, Deep CNN, and EfficientNetB0—to extract a rich and diverse set of features from input images. By fusing these features, the model achieves high classification accuracy and improves generalization across varied datasets.

Experimental evaluation across three datasets—PlantVillage, Plant Leaves, and PlantDoc—demonstrated that the fusion model outperforms individual models, particularly in controlled environments. The integration of a recommendation engine for organic pesticides enhances the system's practicality, providing actionable guidance for sustainable plant disease management.

Overall, this work illustrates the potential of ensemble deep learning models in agricultural diagnostics and provides a meaningful step toward intelligent, accessible, and eco-friendly plant health monitoring.

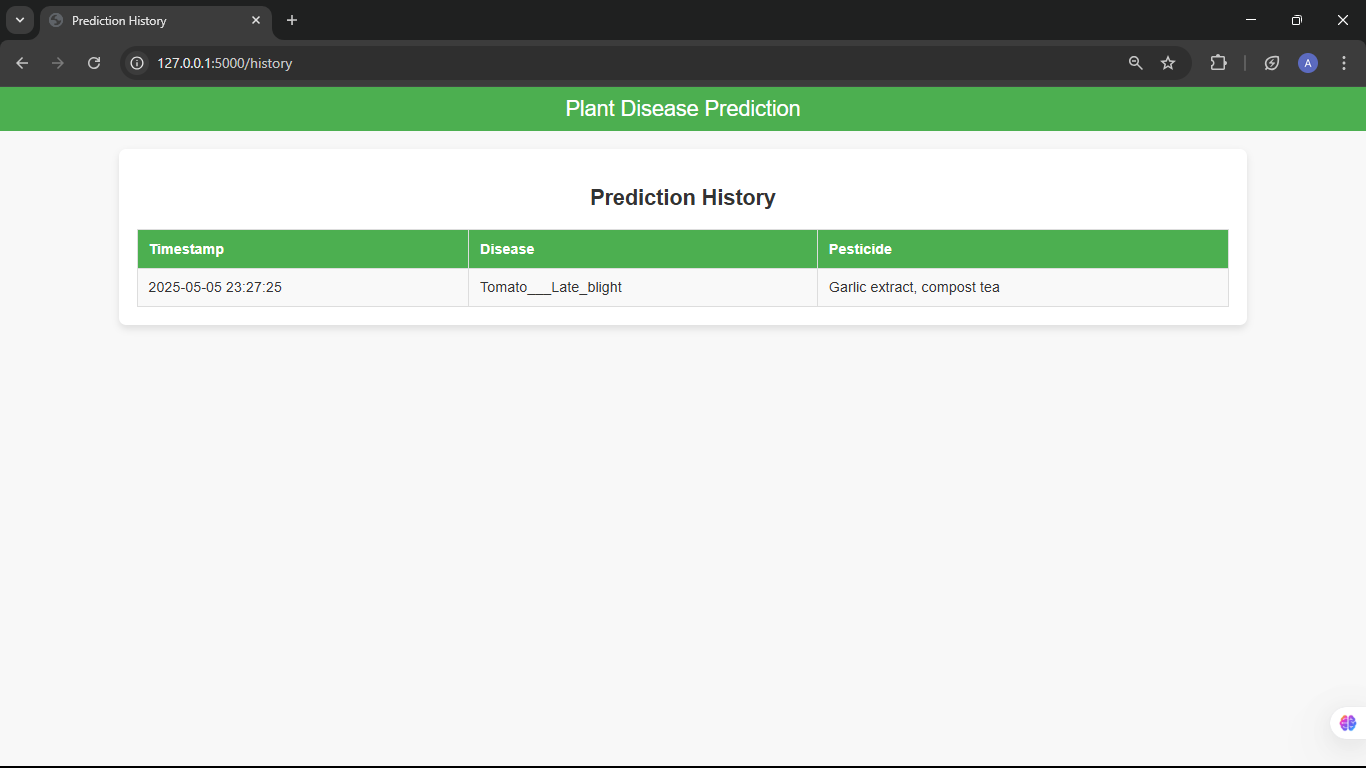
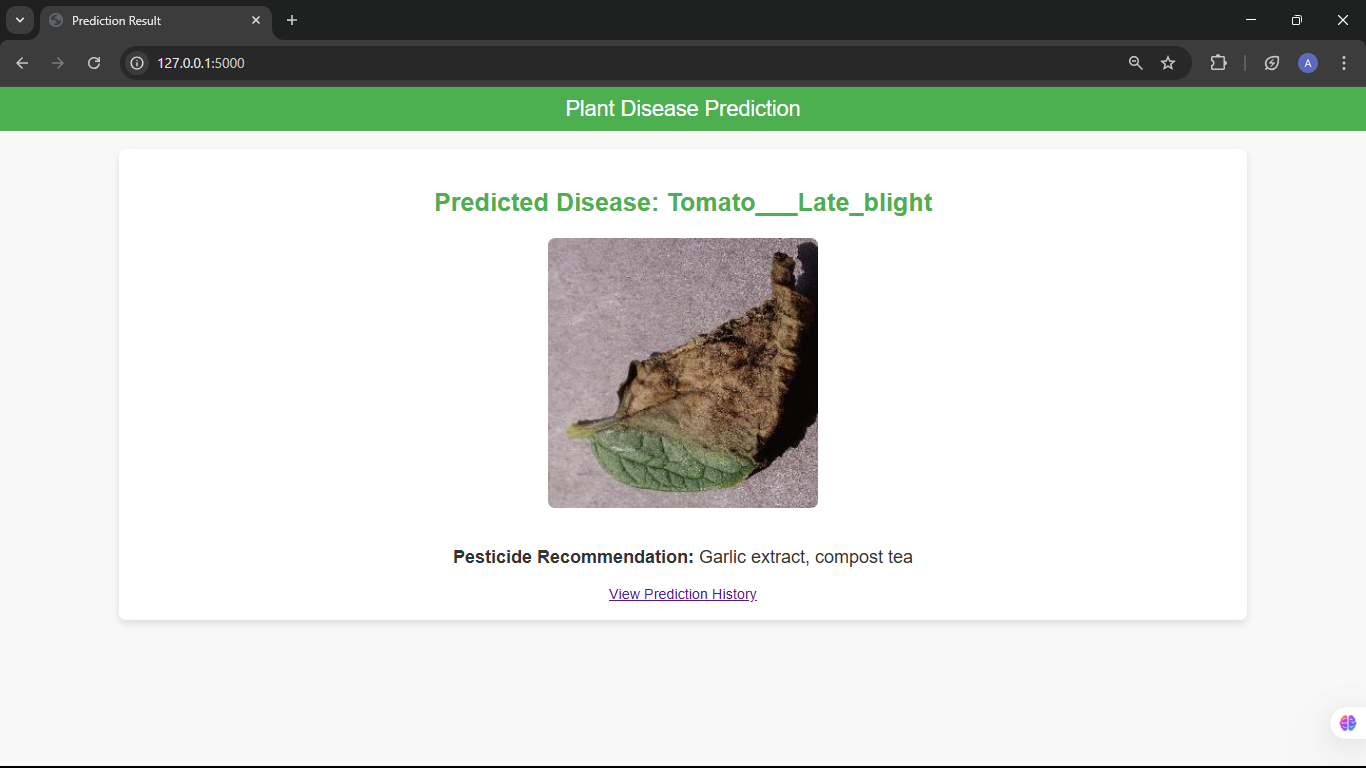
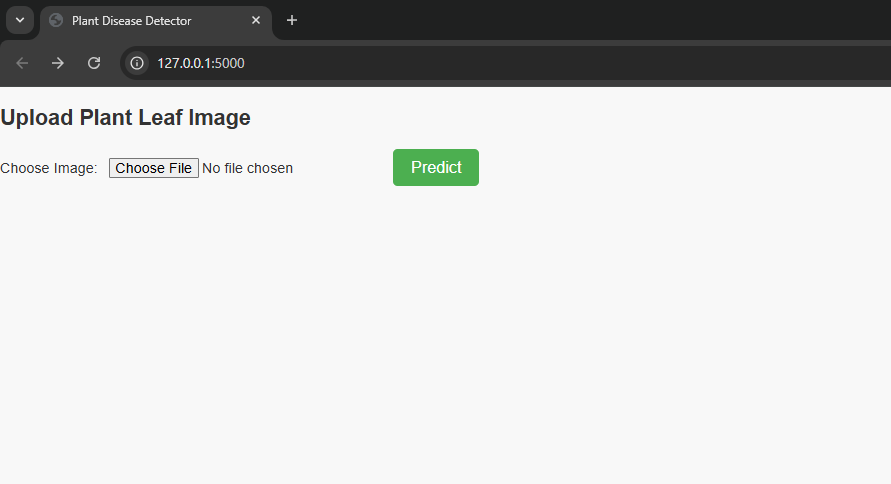
**6.2 Recommendations and Future Work**:

While the developed system has shown considerable promise in controlled and semi-realistic conditions, several improvements can be made to enhance its real-world applicability and scalability:

* Dataset Expansion The current model is trained on a limited range of plant species and disease categories. Expanding the dataset to include more diverse crops and regional disease variants will enhance the model’s adaptability and accuracy across different agricultural zones.
* Temporal Disease Monitoring Introducing temporal data—such as time-lapse images or video sequences—could enable the system to monitor the progression of plant diseases. This would not only improve early detection but also aid in estimating the severity and spread of infections over time.
* Real-World Deployment via Mobile/Web App Although the system is currently operational through a web interface, full-scale deployment remains. Future efforts should focus on developing a lightweight mobile or web application, allowing farmers to capture and upload leaf images on-site and receive real-time predictions and pesticide recommendations.
* Robustness through Domain Adaptation and Augmentation The model’s generalization in uncontrolled environments can be further improved through domain adaptation techniques, such as adversarial learning or transfer learning. Additionally, applying aggressive data augmentation (e.g., noise injection, brightness variation, background clutter) can simulate real-world scenarios during training.

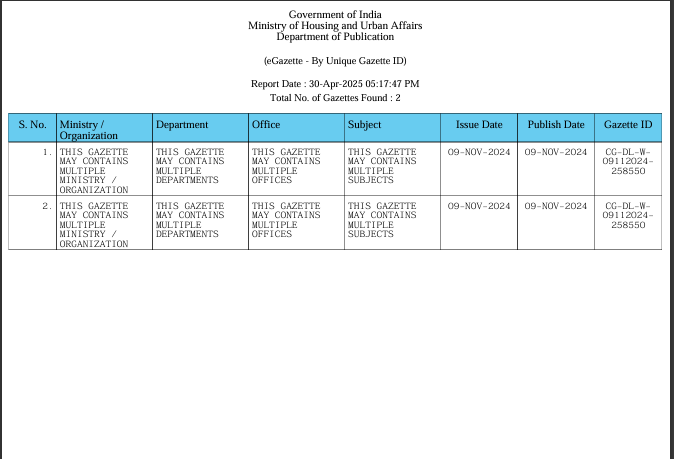
Integration with IoT for Smart Farming Future iterations of the system could integrate with IoT-based agricultural sensors to collect environmental data such as temperature, humidity, and soil moisture. Combining visual leaf data with sensor-based context would enable more accurate and intelligent decision-making, supporting precision agriculture.

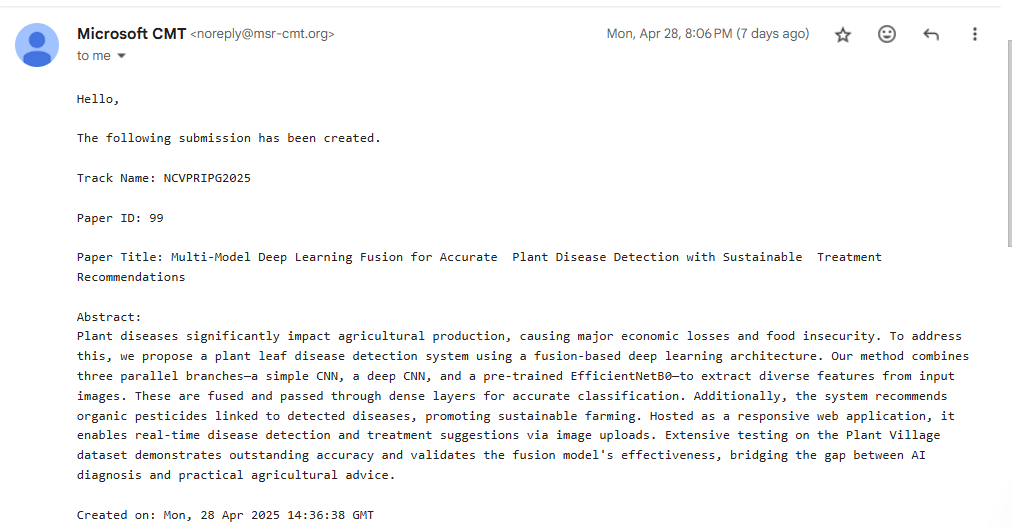
### **6.3 Web Integration**

To ensure accessibility and ease of use for end-users, the proposed plant disease detection and pesticide recommendation system is deployed through a **web-based interface**. The web application is built using a Python-based framework (e.g., Flask or Django) and includes the following features:

**7. PUBLICATION OF THE PAPER**

**7.1 Project Part 1**

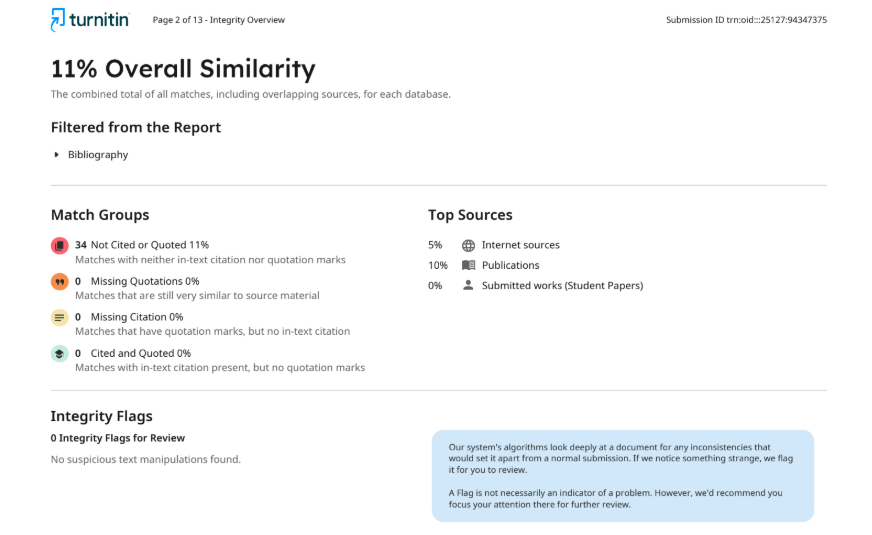




Paper drafted and submitted along with a certificate.

**7.2 Project Part 2**

Communication /Draft paper with Plagiarism Report



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