**Batch: A-3 Roll No.: 16010122104**

**Experiment No 2**

**Group No:**

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| **Title: Literature Survey** |

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**Expected Outcome of Experiment:**

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|  | **At the end of successful completion of the course the student will be able to** |
| CO1 | Define the problem statement and scope of problem |
| CO5 | Prepare a technical report based on the Mini project. |

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**Books/ Journals/ Websites referred:**

**1.**

**2.**

**3.**

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**Chapter 2**

**Literature Survey**

*The Objective of a literature survey is to review existing research, identify gaps, and establish a strong foundation for the study. It helps in understanding key concepts, comparing different approaches, and justifying the need for the current research by analyzing past studies.*

#### Introduction

The development of AI-driven crop disease prediction and management systems represents a critical advancement in modern agriculture. As global food security faces increasing threats from plant diseases, the need for efficient, accurate, and scalable detection methods has become paramount. Traditional approaches to disease identification often rely on manual inspection and expert knowledge, which can be time-consuming, costly, and prone to human error. The integration of artificial intelligence, particularly deep learning techniques, offers a promising solution to these challenges.

This literature survey aims to explore the current state of AI-driven crop disease detection systems, focusing on their methodologies, performance, and practical applications. The primary objectives are to:

* Analyze existing deep learning models and architectures used for plant disease classification.
* Evaluate the effectiveness of various data preprocessing and augmentation techniques.
* Assess the real-world applicability and scalability of AI-based disease detection systems.
* Identify key challenges and areas for future research in this domain.

By reviewing and synthesizing the latest research in this field, we seek to provide a comprehensive understanding of the potential and limitations of AI in crop disease management, guiding future developments and applications in sustainable agriculture.

#### Review of Existing Literature

The application of AI in crop disease detection has evolved rapidly over the past decade, with significant advancements in both methodology and performance.

In 2016, Mohanty et al. demonstrated the potential of convolutional neural networks (CNNs) for plant disease classification, achieving 99.35% accuracy on a dataset of 54,306 images spanning 38 crop-disease pairs. This study highlighted the superiority of deep learning approaches over traditional image processing methods.

Building on this foundation, Hughes and Salathé (2015) developed a mobile-based solution for plant disease detection, emphasizing the importance of accessibility and real-time diagnosis in field conditions. Their work underscored the challenges of deploying AI models in diverse environmental settings.

Ferentinos (2018) further advanced the field by utilizing transfer learning with pre-trained CNN architectures, achieving high accuracy while reducing computational requirements. This approach demonstrated the feasibility of deploying accurate disease detection systems in resource-constrained environments.

Recent studies have focused on specific crops and diseases. Adegbola et al. (2019) developed a machine learning-based model for cassava disease diagnosis, achieving 87% accuracy in classifying diseases like Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBSD).

The integration of IoT devices with AI systems has opened new avenues for real-time monitoring and early warning systems. Koirala et al. (2020) presented a web-based tool that combines disease diagnosis with tailored recommendations, highlighting the importance of user-friendly interfaces in promoting adoption among farmers.

1. **Related Work**

Mohanty et al. (2016) - "Deep Learning for Plant Disease Detection"

Summary: This study utilized CNNs to classify 38 different crop-disease pairs, achieving 99.35% accuracy. The authors used a dataset of 54,306 images and compared the performance of AlexNet and GoogLeNet architectures.

Relevance: Demonstrates the potential of deep learning for accurate plant disease classification.

Comparison: Our proposed system focuses specifically on cassava diseases using a more recent architecture (RexNet-150).

Critical Analysis: The study used controlled images, which may not reflect real-world conditions. Future work should focus on field-based validation.

**Hughes and Salathé (2015) - "PlantVillage: A Mobile-Based Solution for Plant Disease Detection"**

Summary: Developed a mobile application for real-time plant disease diagnosis using image recognition models. The system allowed users to upload leaf images and receive instant feedback.

Relevance: Addresses the need for accessible, user-friendly disease detection tools for farmers.

Comparison: Our system similarly aims for accessibility but uses a web-based interface instead of a mobile app.

Critical Analysis: The study highlighted challenges in handling varying lighting and background conditions, which remain relevant for our project.

**Ferentinos (2018) - "Deep learning models for plant disease detection and diagnosis"**

Summary: Utilized transfer learning with pre-trained CNN architectures to classify plant diseases across multiple crop types. The approach achieved high accuracy while reducing computational requirements.

Relevance: Demonstrates the effectiveness of transfer learning in plant disease detection.

Comparison: Our system also leverages a pre-trained model (RexNet-150) but focuses specifically on cassava diseases.

Critical Analysis: The study emphasized the need for diverse, real-world datasets to improve model generalization, which is a consideration for our project as well.

**Adegbola et al. (2019) - "Cassava Disease Diagnosis Using Machine Learning"**

Summary: Implemented a machine learning model to detect cassava diseases, focusing on CMD and CBSD. The system achieved 87% accuracy using color and texture features from leaf images.

Relevance: Directly addresses cassava disease detection, which is the focus of our project.

Comparison: Our approach uses deep learning instead of traditional machine learning, potentially offering improved feature extraction and accuracy.

Critical Analysis: The reliance on handcrafted features may limit the model's generalizability compared to deep learning approaches.

**Koirala et al. (2020) - "AI-Driven Decision Support for Farmers"**

Summary: Presented a web-based tool combining disease diagnosis with tailored recommendations. The system emphasized user-friendly design to promote adoption among farmers.

Relevance: Highlights the importance of integrating disease detection with actionable insights.

Comparison: Our system similarly aims to provide disease-specific recommendations alongside detection results.

Critical Analysis: The study underscored the need for continuous model updates and localization, which are considerations for the long-term sustainability of our project.

Related Work

1. Francis and Deisy (2019) proposed a CNN model to classify healthy and diseased tomato and apple leaves. The model achieved 87% accuracy using 3,663 images from the PlantVillage dataset.
2. Basavaiah and Anthony (2020) compared various ML approaches for tomato disease detection. Using 200 images across 5 classes, their Random Forest model achieved 94% accuracy.
3. K and Rao (2019) used KNN and probabilistic neural networks to detect tomato leaf diseases, achieving 91.88% accuracy with PNN on 600 field-collected images.
4. Vadivel and Suguna (2022) developed an optimized BPNN model for tomato disease classification, achieving 99.4% accuracy on an augmented dataset of 10,000 images.
5. Chakravarthy and Raman (2020) used fine-tuned ResNet and Xception models to detect early blight in tomato leaves, achieving 99.95% accuracy on 4,281 images.
6. Kumar and Vani (2019) compared CNN architectures for tomato disease detection, with VGG16 achieving 99.25% accuracy on 14,903 PlantVillage images.
7. Mustafa et al. (2023) developed an optimized CNN model for pepper bell leaf disease classification, achieving 99.99% accuracy on an augmented dataset of 20,000 images.
8. Lin et al. (2019) used a U-Net architecture to detect powdery mildew in cucumber leaves, achieving 83.45% dice accuracy.
9. Khan et al. (2020) developed a multi-class SVM model for cucumber disease classification, achieving 98.08% accuracy.
10. Zhang et al. (2019) proposed a Global Pooling Dilated CNN (GPDCNN) for cucumber disease detection, achieving 94.65% accuracy.

Now, based on these summaries, I will create the Literature Survey Table:

| **Author(s) & Year** | **AI Method** | **Dataset** | **Crop** | **Diseases** | **Accuracy** |
| --- | --- | --- | --- | --- | --- |
| Francis and Deisy (2019) | CNN | PlantVillage (3,663 images) | Tomato, Apple | Leaf spot, Mosaic virus | 87% |
| Basavaiah and Anthony (2020) | Random Forest | PlantVillage (200 images) | Tomato | Bacterial, Septoria, Spider mite, Target spot | 94% |
| K and Rao (2019) | Probabilistic Neural Network | Self-collected (600 images) | Tomato | Miners, Verticillium wilt, Spider mites, Powdery mildew | 91.88% |
| Vadivel and Suguna (2022) | BPNN | Augmented (10,000 images) | Tomato | Bacterial spot, Mosaic, Septoria, Yellow curl | 99.4% |
| Chakravarthy and Raman (2020) | ResNet, Xception | PlantVillage (4,281 images) | Tomato | Early blight | 99.95% |
| Kumar and Vani (2019) | VGG16 | PlantVillage (14,903 images) | Tomato | Target spot, Mosaic, Septoria, Leaf mould | 99.25% |
| Mustafa et al. (2023) | Optimized CNN | Augmented (20,000 images) | Pepper bell | Multiple diseases | 99.99% |
| Lin et al. (2019) | U-Net | Kaggle dataset | Cucumber | Powdery mildew | 83.45% |
| Khan et al. (2020) | Multi-class SVM | Self-collected | Cucumber | Downy mildew, Bacterial angular, Corynespora, Scab, Gray mold, Anthracnose, Powdery mildew | 98.08% |
| Zhang et al. (2019) | GPDCNN | Self-collected | Cucumber | Anthracnose, Gray mold, Angular leaf spot, Black spot | 94.65% |

#### 4. Research Gaps and Challenges

Despite significant advancements in AI-driven crop disease detection, several key challenges and research gaps remain:

1. Real-world applicability: Many studies use controlled datasets, which may not reflect the variability of field conditions. There is a need for robust models that can handle diverse lighting, backgrounds, and image qualities.
2. Scalability across crops and regions: Most systems focus on specific crops or regions. Developing scalable solutions that can be easily adapted to different crops and geographical areas remains a challenge.
3. Early detection capabilities: Current systems often detect diseases at advanced stages. Research is needed to improve early detection of diseases before visible symptoms appear.
4. Integration with other data sources: Combining image-based detection with other data sources (e.g., weather data, soil sensors) could improve prediction accuracy but presents challenges in data integration and model complexity.
5. Explainability and trust: As AI systems become more complex, there is a growing need for explainable AI to build trust among farmers and stakeholders.
6. Resource constraints: Developing lightweight models that can run on low-resource devices without compromising accuracy remains an ongoing challenge.
7. Continuous learning and adaptation: Creating systems that can continuously learn and adapt to new diseases or variations without requiring complete retraining is an area for future research.
8. Ethical and privacy considerations: As these systems collect and process large amounts of agricultural data, addressing privacy concerns and ensuring ethical use of the technology is crucial.

In conclusion, while AI-driven crop disease detection has shown great promise, addressing these challenges will be critical for widespread adoption and impact in global agriculture. Future research should focus on developing more robust, scalable, and user-centric solutions that can effectively support sustainable farming practices across diverse agricultural contexts.