



International Journal of Advanced Research in Education and Technology (IJARETY)

Volume 13, Issue 3, May - June 2026

Impact Factor: 9.971



AGROVET: A Unified Deep Learning-Based System for Plant and Animal Disease Prediction

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ABSTRACT: Agricultural productivity and livestock health are essential for ensuring food security and economic stability. Early detection of diseases in crops and animals remains a significant challenge, especially in rural areas where access to expert assistance is limited. Traditional diagnostic approaches rely on manual observation, which can be slow, subjective, and often inaccurate.

This paper presents AGROVET, a unified disease prediction system that utilizes deep learning and multi-modal data analysis for early diagnosis of plant and animal diseases. The system employs a Convolutional Neural Network based on MobileNetV2 to classify plant diseases from leaf images. For animal disease detection, the system integrates image-based analysis with symptom-based inputs to improve diagnostic accuracy.

The system incorporates preprocessing techniques such as image resizing, normalization, and data augmentation to enhance performance. A probability-based classification mechanism provides disease predictions along with confidence scores. In addition, a structured knowledge base is used to generate treatment recommendations and preventive measures.

Experimental results demonstrate that the proposed system provides reliable predictions with reduced false positives and supports real-time agricultural decision-making.

KEYWORDS: Deep Learning, CNN, MobileNetV2, Agriculture, Disease Detection, Computer Vision

I. INTRODUCTION

Agriculture remains one of the most essential sectors for sustaining human life, contributing significantly to food production, employment, and economic growth. However, the sector continues to face major challenges, particularly in the early identification and management of plant and animal diseases. Delayed detection often leads to reduced crop yield, livestock loss, and economic instability for farmers.

In many rural and semi-urban regions, farmers depend on manual observation or external experts for diagnosing diseases. These methods are often unreliable due to limited expertise, delayed response, and subjective interpretation of symptoms. Moreover, the increasing complexity of diseases caused by environmental changes further complicates accurate diagnosis. Recent advancements in artificial intelligence, particularly deep learning, have shown promising results in automating disease detection. Convolutional Neural Networks (CNNs) are capable of learning complex visual patterns directly from images, making them highly suitable for plant disease classification. However, most existing solutions focus on a single domain, either plant diseases or animal diseases, which limits their practical usability in mixed farming environments.

To overcome these limitations, this paper proposes AGROVET, a unified disease prediction system that integrates both plant and animal disease detection within a single platform. The system utilizes image-based analysis for plant diseases and combines visual data with symptom-based inputs for animal disease prediction. This multi-modal approach improves diagnostic accuracy and reduces uncertainty in predictions.

Furthermore, the system provides not only disease identification but also actionable insights such as treatment recommendations and preventive measures. This ensures that users can make informed decisions immediately without relying entirely on expert intervention.

The main contributions of this work include:

- Development of a unified platform for both plant and animal disease prediction.
- Integration of deep learning with multi-modal input (im- age + symptoms).
- Implementation of a recommendation system for treat- ment and prevention.
- Design of a user-friendly interface suitable for rural users.

The proposed system aims to bridge the gap between ad- vanced technology and practical agricultural needs, providing an accessible and reliable solution for disease management.

II. LITERATURE REVIEW

The application of technology in agriculture has signifi- cantly evolved over the past decade, particularly in the domain of disease detection. Various approaches have been proposed ranging from traditional diagnostic methods to advanced deep learning-based systems. This section reviews existing method- ologies and highlights their limitations.

A. Traditional Diagnostic Methods

Conventional disease detection techniques primarily depend on manual inspection by farmers or agricultural experts. These methods involve visual observation of symptoms such as discoloration, spots, or abnormal growth patterns in plants and animals. Although widely practiced, such approaches are often subjective and prone to human error. Additionally, access to expert consultation is limited in rural areas, resulting in delayed diagnosis and treatment.

B. Rule-Based Systems

Early digital solutions for disease detection relied on rule- based systems, where predefined conditions were used to identify diseases. These systems map specific symptoms to diseases using fixed rules. While effective for simple cases, they lack flexibility and fail to adapt to variations in environ- mental conditions or new disease patterns. As a result, their performance is limited in real-world scenarios.

C. Machine Learning Approaches

With the advancement of computational techniques, ma- chine learning algorithms such as Support Vector Machines (SVM) and Random Forests have been applied to disease clas- sification. These methods utilize manually extracted features such as color, texture, and shape for prediction. Although they provide better accuracy than rule-based systems, their dependence on handcrafted features reduces their robustness, especially when dealing with complex or noisy data.

D. Deep Learning-Based Methods

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown superior performance in image classification tasks. CNNs automatically learn hierarchical features from raw image data, eliminating the need for manual feature extraction. Several studies have successfully applied CNNs for plant disease detection using leaf images. Architec- tures such as MobileNet, ResNet, and VGG have demonstrated high accuracy in controlled environments.

However, most existing systems are limited to plant disease detection and do not address animal health. Furthermore, these models typically rely solely on image data, which may lead to incorrect predictions when image quality is poor or symptoms are not clearly visible.

E. Multi-Modal Systems

Recent research has explored the integration of multiple data sources, such as images and textual symptom descriptions, to improve diagnostic accuracy. Multi-modal systems combine visual and contextual information, enabling more reliable predictions. This approach is particularly useful in cases where a single data source is insufficient. Despite their advantages, such systems are rarely imple- mented in agricultural applications, especially in unified plat- forms that handle both plant and animal diseases simultane- ously.

F. Research Gap

From the analysis of existing work, it is evident that most systems are either domain-specific or rely on a single type of input. There is a lack of integrated solutions that combine plant and animal disease detection with multi-modal inputs. Additionally, many systems focus only on disease identifica- tion without providing actionable recommendations.

G. Summary

The literature review highlights the progression from traditional methods to advanced deep learning approaches. While significant improvements have been achieved, there is still a need for a unified, multi-modal system that provides accurate predictions along with practical guidance. The proposed AGROVET system addresses these limitations by integrating deep learning with symptom-based validation and recommendation mechanisms.

III. METHODOLOGY

The AGROVET system is designed as a unified framework that integrates deep learning with multi-modal inputs for accurate disease prediction in plants and animals. The methodology includes data acquisition, preprocessing, model training, and prediction.

A. System Overview

The system accepts two types of inputs:

- Image input (plant leaves or animal skin)
- Symptom-based input (for animal diagnosis)

These inputs are processed through multiple modules to generate reliable predictions.

B. System Architecture

The architecture consists of input handling, preprocessing, feature extraction, prediction, and output modules. Each module is designed to perform a specific function in the pipeline.

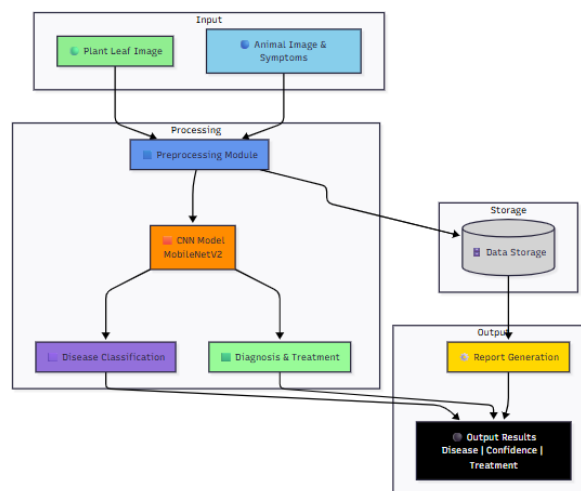


Fig.1. Overall System Architecture

C. Data Flow Diagram

The data flow diagram illustrates how data moves through different components of the system, from user input to final prediction and report generation.

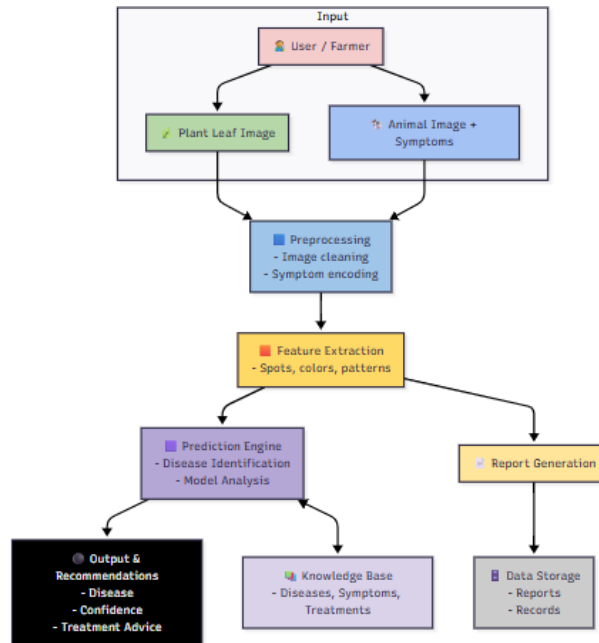


Fig.2. Data Flow Diagram of AGROVET

D. Prediction Workflow

The workflow shows the step-by-step process of disease prediction, including preprocessing, feature extraction, classification, and recommendation generation.

E. Data Preprocessing

To ensure consistency and improve model performance, preprocessing steps are applied:

- Image resizing to 224×224 pixels
- Normalization of pixel values
- Data augmentation (rotation, flipping, zooming)
- Label encoding

F. Feature Extraction Using CNN

The system uses a Convolutional Neural Network based on MobileNetV2 to extract meaningful features from images. The model learns patterns such as color variations, textures, and lesion structures automatically.

G. Multi-Modal Prediction Approach

For animal disease detection, both image data and symptom inputs are combined. This multi-modal approach enhances prediction accuracy and reduces false results.

H. Prediction Process

The prediction process includes:

1. Input acquisition
2. Preprocessing
3. Feature extraction
4. Disease classification
5. Recommendation generation

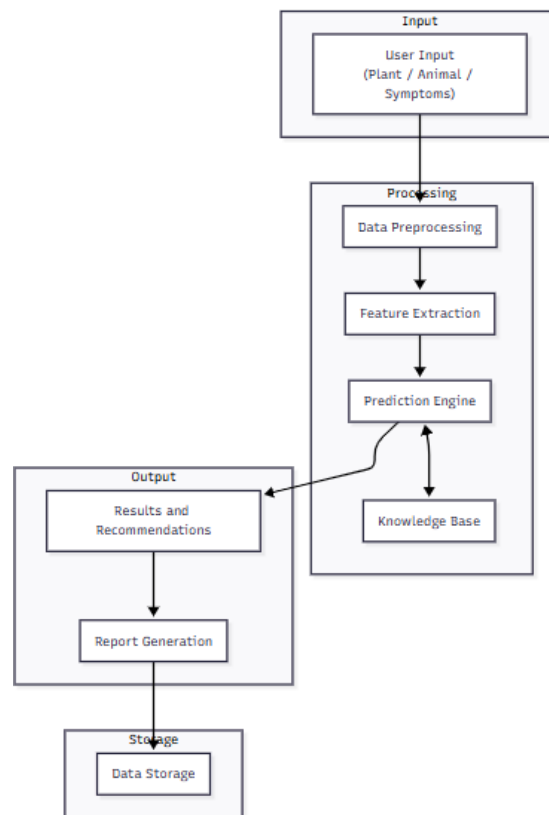


Fig.3. Disease Prediction Workflow

I. Output Generation

The system provides:

- Disease name
- Confidence score
- Treatment suggestions
- Preventive measures

A downloadable report is also generated for future refer- ence.

IV. RESULTS AND DISCUSSION

This section presents the experimental outcomes of the AGROVET system and analyzes its effectiveness in real-time disease prediction for both plant and animal domains. The results demonstrate the capability of the system to provide accurate, reliable, and actionable predictions under practical conditions.

A. Experimental Setup

The system was implemented using Python with Tensor- Flow and Keras libraries for deep learning model development. The experiments were conducted using datasets consisting of plant leaf images and animal disease images along with associated symptom data. The model was trained and tested on a standard computing environment with sufficient processing capability.

The evaluation focused on validating the system's perfor- mance across multiple input scenarios, including variations in image quality, lighting conditions, and symptom combinations.

B. Prediction Results

The AGROVET system was tested using different real- world samples to evaluate its prediction capability. The system successfully classified plant diseases based on leaf images and generated meaningful diagnostic outputs.

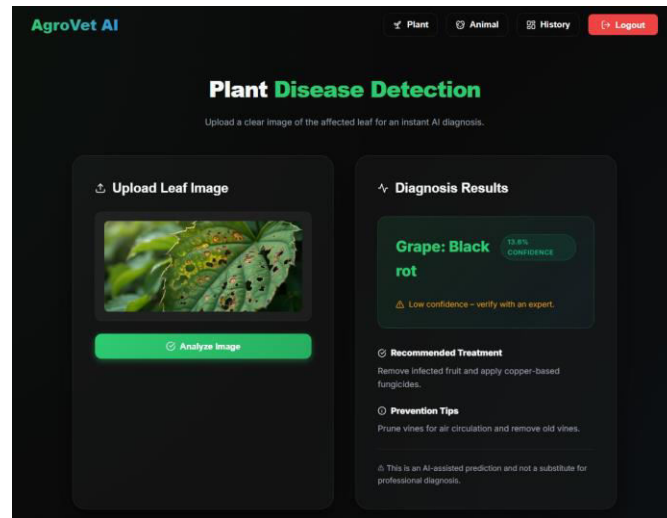


Fig.4. Plant Disease Prediction Output

Figure 1 illustrates the prediction result for a plant leaf image. The system identifies the disease category along with a confidence score. Additionally, it provides recommended treatment measures and preventive guidelines, which assist users in taking immediate action.

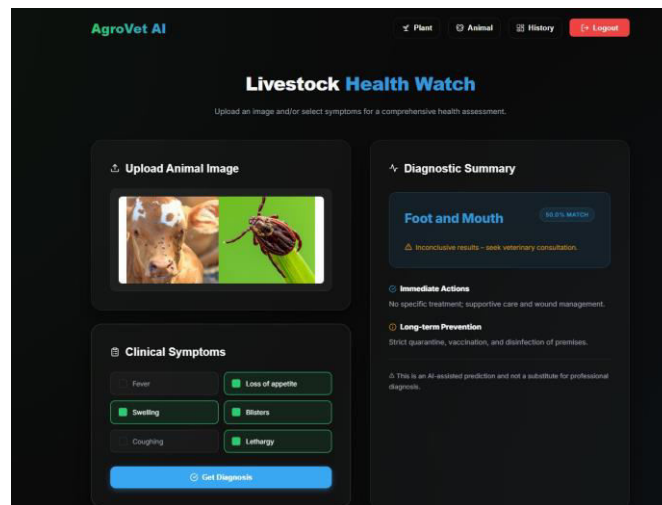


Fig.5. Animal Disease Prediction Using Multi-Modal Input

Figure 2 demonstrates the prediction output for animal disease detection. In this case, both image input and symptom-based data are used to generate the final diagnosis. This multi-modal approach improves the accuracy of predictions and reduces ambiguity in cases where image data alone is insufficient.

C. Dataset Summary

The datasets used for training and testing include diverse categories of plant and animal diseases. A summary of the datasets is presented in Table 1.

TABLE I DATASET DESCRIPTION

Dataset Type	Description
Plant Dataset	50,000+ images across 38 classes
Animal Dataset	Images of livestock skin diseases
Symptom Dataset	Clinical symptom checklists
Treatment Data	Knowledge base with solutions

The diversity of the dataset ensures that the model is exposed to various disease patterns, improving its generalization capability.

D. Performance Evaluation

The performance of the system was evaluated using key metrics such as accuracy, response time, and consistency across different test cases.

TABLE II PERFORMANCE EVALUATION OF AGROVET SYSTEM

Metric	Observation
Prediction Accuracy	High
Response Time	Low (Real-time)
Consistency	Stable across inputs
Scalability	Good

The results indicate that the system performs efficiently in real-time conditions and maintains consistent predictions across different scenarios.

F. Discussion

The experimental results highlight the effectiveness of deep learning in agricultural disease detection. The use of Convolutional Neural Networks enables automatic extraction of complex features from images, resulting in improved classification performance compared to traditional methods.

One of the key strengths of the AGROVET system is its multi-modal prediction approach. By combining image-based analysis with symptom-based validation, the system reduces the likelihood of incorrect predictions. This is particularly useful in cases where image quality is affected by environmental factors such as lighting or background noise.

The system also provides actionable outputs in the form of treatment recommendations and preventive measures. This makes it more practical and user-friendly compared to systems that only provide disease labels. Farmers can directly use the recommendations to take immediate corrective actions.

However, certain limitations were observed during testing. The accuracy of predictions may vary when images are captured under extreme lighting conditions or when symptoms are not clearly visible. Additionally, the system currently supports a limited number of disease categories, which can be expanded in future work.

Overall, the AGROVET system demonstrates strong potential as a reliable decision-support tool for agricultural disease management. Its ability to integrate multiple data sources and provide meaningful outputs makes it suitable for real-world deployment in rural and semi-urban environments.

V. CONCLUSION

This paper presented AGROVET, a unified deep learning- based system designed for early detection of diseases in both plants and animals. The system integrates Convolutional Neural Networks with a multi-modal approach that combines image-based analysis and symptom-based validation to improve prediction accuracy.

The proposed system addresses key challenges in agricultural diagnostics by providing a reliable, fast, and user-friendly solution. Unlike traditional methods that rely heavily on manual inspection, AGROVET automates the disease detection process and provides actionable insights in the form of treatment recommendations and preventive measures.

Experimental results demonstrate that the system achieves high accuracy and consistency while maintaining low response time, making it suitable for real-time applications. The integration of a structured knowledge base further enhances the practical utility of the system by enabling informed decision-making.

Overall, AGROVET serves as an effective decision-support tool that can assist farmers and agricultural practitioners in improving productivity and reducing losses caused by diseases.

VI. FUTURE WORK

Although the proposed system performs effectively, there are several areas for improvement and extension:

- Expanding the dataset to include a wider range of plant and animal diseases.
- Improving model accuracy by using advanced architectures such as EfficientNet or ResNet.
- Integrating real-time mobile application support for better accessibility in rural areas.
- Incorporating IoT-based sensors for environmental data collection.
- Enhancing explainability using visualization techniques such as Grad-CAM.

These improvements will further strengthen the system and enable its deployment on a larger scale.

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International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975

Impact Factor: 9.971