International Journal of Emerging Research in Science, Engineering, and Management
Vol. 2, Issue 3, pp.213-222, March 2026.
www.ijersem.com eISSN- 3107-9075

NLP-Based Approach for Tomato Leaf Disease Prediction and Classification

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Abstract: Early identification of tomato leaf diseases is essential to minimize crop loss and improve agricultural productivity. Traditional disease diagnosis methods rely heavily on manual inspection, which is time-consuming, subjective, and requires expert knowledge. To overcome these limitations, this work presents an NLP-based intelligent approach combined with deep learning for tomato leaf disease prediction and classification. The proposed system utilizes a structured workflow that begins with dataset acquisition, followed by preprocessing, feature extraction, and classification. A pre-trained MobileNetV2 deep learning model is employed for effective feature learning and disease recognition. The model is trained using labeled tomato leaf images representing multiple disease categories, such as early blight, late blight, leaf mold, bacterial spot, and target spot. The extracted features are analyzed through deep neural layers to generate accurate predictions. Experimental results demonstrate that the proposed system achieves 75% classification accuracy, with a precision of 81.15% and a recall of 70.33%, indicating reliable disease detection performance. The model successfully identifies disease types and generates detailed diagnostic reports, including disease name, confidence score, symptoms, severity level, and recommended treatment measures. Visual performance analysis using accuracy and loss curves confirms stable convergence and effective learning behaviour. The developed system offers a practical, automated, and scalable solution for tomato disease diagnosis, reducing dependency on manual inspection and expert intervention. The integration of deep learning with structured output reporting makes the system suitable for real-world agricultural applications and future deployment in smart farming environments.

Keywords: Medical Image Security, Wavelet-Assisted Steganography, Visual Secret Sharing, DICOM Images, Privacy Preservation.

1 INTRODUCTION

Tomato is one of the most widely cultivated vegetable crops worldwide and plays a vital role in agricultural productivity and food security. However, tomato cultivation is highly susceptible to various diseases such as early blight, late blight, leaf curl virus, and target spot, which significantly reduce yield and crop quality if not detected at an early stage. Traditional disease identification methods rely on visual inspection and expert knowledge, which are time-consuming, subjective, and impractical for large-scale farming environments. Several studies have shown that plant diseases are strongly influenced by microbial infections, viral transmission through vectors, and environmental conditions, making early detection critical for effective disease management [1]-[3]. Recent advancements in artificial intelligence and machine learning have enabled automated disease detection using image-based and sensor-based approaches. Techniques such as convolutional neural networks, deep learning, and hyperspectral imaging have been successfully applied for plant disease classification [4]-[5].

However, most existing systems depend heavily on image datasets, which require controlled lighting conditions, high-quality cameras, and large annotated datasets. These limitations restrict their applicability in real-world agricultural environments, particularly in rural areas. To overcome these challenges, Natural Language Processing (NLP) has emerged as an effective alternative by enabling disease analysis using agricultural text data such as farmer queries, research articles, expert reports, and advisory bulletins. NLP-based systems can extract disease symptoms, causes, and treatment information from unstructured text and support intelligent decision-making without relying solely on images. Previous studies have demonstrated the effectiveness of text mining, machine learning, and deep learning models in extracting meaningful patterns from agricultural datasets [6].

However, limited research has focused on applying NLP specifically for tomato leaf disease prediction and classification. Moreover, recent advances in deep learning architectures, including CNNs, attention-based models, and generative approaches, have shown promising performance in disease detection and feature extraction tasks [7]. Studies on plant virus behavior, resistance breeding, and pathogen transmission mechanisms further highlight the importance of accurate disease identification for crop protection and yield enhancement [8]. Despite these advancements, there remains a gap in developing an integrated NLP-driven framework that can effectively analyze textual agricultural data and provide reliable disease classification and prediction.

The scope of this project is to develop an NLP-based intelligent system for tomato leaf disease prediction and classification using agricultural textual data. The system focuses on analyzing symptom descriptions, disease-related reports, and expert knowledge instead of relying on image-based inputs. It aims to support farmers, researchers, and agricultural advisors by providing fast, reliable, and scalable disease identification. The proposed framework can be extended to other crops and integrated with IoT or decision-support platforms for real-time agricultural monitoring [9]. The primary objectives of this work are:

1. To design an NLP-based framework for tomato leaf disease detection using textual data.
2. To preprocess agricultural text data using tokenization, normalization, and feature extraction techniques.
3. To apply machine learning and deep learning models for disease classification.
4. To analyze and classify major tomato diseases such as early blight, late blight, and leaf curl disease.
5. To improve disease prediction accuracy while reducing dependency on image-based datasets.
6. To support farmers with timely and knowledge-driven disease diagnosis.

The key contributions of this work are summarized as follows:

- Development of a novel NLP-based approach for tomato leaf disease prediction using textual agricultural data.
- Implementation of feature extraction and classification techniques for disease identification.
- Reduction of dependency on image-based diagnosis systems.
- Comparative analysis with existing disease detection approaches.
- A scalable and cost-effective solution suitable for real-world agricultural applications.

The remainder of this paper is organized as follows. Section 2 presents a detailed literature review, discussing existing techniques related to medical image security, steganography, visual secret sharing, and their limitations. Section 3 describes the proposed method, including the system architecture, wavelet-based steganography, and visual secret sharing process used for secure medical image exchange. Section 4 discusses simulation results and performance analysis, including PSNR, SSIM, histogram analysis, and comparison with existing methods. Finally, Section 5 concludes the paper and outlines the future scope, highlighting possible enhancements and directions for further research.

2 LITERATURE SURVEY

He et al. investigated the replication mechanism of plant DNA viruses inside insect vectors and demonstrated that the virus utilizes the host's DNA synthesis machinery within the salivary glands [1]. Their study revealed critical biological interactions responsible for virus transmission, providing valuable insights into plant virus propagation and vector-based disease spread, which is essential for understanding tomato virus infections at a molecular level. Choi et al. employed metatranscriptomic analysis to identify viruses and viroids affecting tomato and pepper crops in Vietnam [2]. Their work successfully detected multiple viral strains from infected samples, highlighting the effectiveness of RNA sequencing techniques for large-scale plant disease surveillance and early diagnosis in agricultural ecosystems. Babu et al. proposed a real-time crop monitoring system using machine learning techniques to detect plant diseases and track crop growth [3]. The system utilized sensor data and classification models to identify disease symptoms efficiently, demonstrating how intelligent automation can improve crop management and reduce manual inspection efforts. Ghanim et al. provided experimental evidence of transovarial transmission of the tomato yellow leaf curl virus through the whitefly Bemisia tabaci [4]. Their findings confirmed that viral persistence across generations contributes to rapid disease spread, emphasizing the importance of early detection and vector control strategies in tomato farming.

Dhaliwal et al. presented a comprehensive review of tomato yellow leaf curl virus, discussing disease symptoms, transmission patterns, and resistance breeding strategies [5]. The study emphasized genetic resistance as an effective long-term solution for disease management and highlighted challenges in conventional breeding approaches. Mohebbanaaz et al. introduced a Conditional Generative Adversarial Network (CGAN) for detecting fake images [6]. Although focused on image forgery detection, the study demonstrated the effectiveness of deep generative models, which can be extended for data augmentation in plant disease datasets to improve model robustness. Nowicki et al. provided an extensive overview of late blight disease caused by Phytophthora infestans, explaining its pathology, epidemiology, and resistance breeding strategies [7]. Their work remains a foundational reference for understanding disease progression and host-pathogen interactions in tomato crops.

Mohebbanaaz et al. developed a recurrent neural network-based model for automated cardiac arrhythmia detection [8]. The study demonstrated how deep learning can efficiently classify complex biological signals, supporting the applicability of similar learning architectures for plant disease pattern recognition. Wu et al. proposed a DCGAN-based data augmentation technique to improve tomato leaf disease classification accuracy [9]. By synthetically generating disease images, the study addressed data scarcity issues and significantly enhanced classification performance, making it relevant for disease detection systems with limited datasets. Buziashvili et al. developed transgenic tomato lines expressing human lactoferrin, which showed increased resistance to bacterial and fungal infections [10]. Their research demonstrated the role of genetic modification in improving plant immunity and reducing dependency on chemical treatments.

Table 1. Summary of Literature Survey

Work	Author & Year	Method / Technique	Key Contribution	Limitation
[1]	He et al., 2020	Molecular & biological analysis	Demonstrated replication of plant DNA virus inside insect vectors	No computational or automated disease detection
[2]	Choi et al., 2020	Metatranscriptomics	Identified viruses and viroids affecting tomato and pepper crops	High computational cost, lab-dependent
[3]	Babu et al., 2024	Machine Learning	Real-time crop growth monitoring and disease detection	Dependent on sensor accuracy
[4]	Ghanim et al., 1998	Biological transmission study	Proved transovarial virus transmission in whiteflies	No disease prediction mechanism
[5]	Dhaliwal et al., 2020	Review on resistance breeding	Summarized management of tomato leaf curl virus	No automation or AI integration
[6]	Mohebbanaaz et al., 2024	CGAN-based deep learning	Identified fake images using GANs	Not directly applied to agriculture
[7]	Nowicki et al., 2012	Disease pathology study	Detailed analysis of late blight disease	Manual diagnosis-based
[8]	Mohebbanaaz et al., 2021	RNN-based classification	Automated arrhythmia detection	Healthcare-focused, not agricultural
[9]	Wu et al., 2020	DCGAN + CNN	Data augmentation for tomato disease detection	Requires large training data
[10]	Buziashvili et al., 2020	Genetic engineering	Improved resistance using transgenic tomato	Costly and complex implementation
[11]	Sladojevic et al., 2016	Deep CNN	Leaf disease recognition using images	Needs high-quality images
[12]	Ronneberger et al., 2015	U-Net CNN	Image segmentation for biomedical data	High computation overhead
[13]	Schlub et al., 2007	Disease survey	Overview of tomato target spot disease	No automated analysis
[14]	Mohebbanaaz et al., 2024	Attention-based CNN	Improved feature learning using attention	Requires large dataset
[15]	Pernezny et al., 2002	Chemical control study	Disease control using fungicides	Environmental impact
[16]	Mohebbanaaz et al., 2021	Decision Tree + Boosting	Improved ECG classification	Domain-specific
[17]	Abdulridha et al., 2020	Hyperspectral imaging	UAV-based disease detection	Expensive hardware
[18]	Mohebbanaaz et al., 2021	Deep CNN + SVM	High-accuracy disease detection	Needs feature tuning
[19]	Mohebbanaaz et al., 2021	GAN-based noise removal	Improved signal clarity	Not agriculture-focused
[20]	Pranathi et al., 2018	CNN	Automated tomato leaf disease detection	Limited generalization

Sladojevic et al. presented one of the earliest deep learning-based plant disease recognition models using convolutional neural networks [11]. Their approach achieved high accuracy in leaf image classification and laid the foundation for modern deep learning-based agricultural diagnostic systems. Ronneberger et al. introduced the U-Net architecture for biomedical image segmentation, which later became widely adopted in agricultural imaging applications [12]. The encoder-decoder structure proved effective in extracting fine-grained features, making it suitable for plant disease segmentation tasks. Schlub et al. analyzed target spot disease in tomatoes caused by Corynespora cassiicola, discussing its symptoms, epidemiology, and environmental conditions favoring its spread [13]. Their findings contributed to improved disease diagnosis and management strategies. Mohebbanaaz et al. proposed an attention-based CNN architecture (AttCNNnet) for detecting epileptic seizures from EEG signals [14]. The attention mechanism enhanced feature learning, demonstrating its effectiveness for complex pattern recognition tasks that can be adapted for plant disease classification.

Pernezny et al. studied various control strategies for tomato target spot disease, including fungicides and biological agents [15]. Their experimental results highlighted the importance of integrated disease management practices in improving crop health and yield. Mohebbanaaz et al. developed an optimized decision tree and adaptive boosting approach for ECG signal classification [16]. The study demonstrated improved classification accuracy, showing the effectiveness of hybrid machine learning techniques for biomedical and agricultural data analysis.

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www.ijersem.com eISSN- 3107-9075

Abdulridha et al. utilized UAV-based hyperspectral imaging for detecting tomato diseases such as bacterial spot and target spot [17]. Their work demonstrated the potential of remote sensing and spectral analysis for large-scale, non-invasive crop monitoring. Mohebbanaaz et al. proposed a deep CNN combined with optimized SVM for cardiac arrhythmia detection [18]. The hybrid approach achieved high accuracy, reinforcing the usefulness of deep learning classifiers for pattern-based disease detection tasks. Mohebbanaaz et al. introduced a residual GAN-based approach for noise removal in ECG signals [19]. The model effectively enhanced signal quality, demonstrating the applicability of generative networks in preprocessing noisy biological data, which can also benefit agricultural data analysis. Tm et al. developed a CNN-based tomato leaf disease detection system using image classification techniques [20]. Their study achieved reliable classification performance and highlighted the effectiveness of deep learning in automating plant disease diagnosis.

From the existing literature, it is evident that most tomato disease detection approaches rely heavily on image-based deep learning techniques, such as CNNs, DCGANs, and hyperspectral imaging. Although these methods provide good accuracy, they suffer from several limitations:

- Dependence on large labeled image datasets
- High computational and hardware requirements
- Sensitivity to lighting and image quality
- Limited use of agricultural textual data
- Lack of knowledge-driven decision support

Very few studies explore Natural Language Processing (NLP) for agricultural disease analysis, despite the availability of rich textual data such as research articles, farmer reports, and agricultural advisories. Existing NLP-based works focus mainly on medical or generic text classification and not on crop disease prediction.

3 Proposed Method

The proposed system introduces an NLP-based approach for tomato leaf disease prediction and classification by utilizing agricultural text data such as research articles, disease reports, and farmer queries. Initially, the input text data is collected and pre-processed using NLP techniques, including tokenization, stop-word removal, stemming, and lemmatization, to enhance data quality. Feature extraction is then performed using text vectorization techniques such as TF-IDF or word embeddings to capture semantic information related to plant diseases. The extracted features are fed into machine learning and deep learning classifiers for disease prediction. The model learns disease-specific patterns from textual descriptions and classifies the input into various tomato diseases, such as early blight, late blight, and leaf spot. Unlike conventional image-based approaches, the proposed method efficiently works with textual data, making it scalable, lightweight, and suitable for real-time agricultural advisory systems. The system ultimately provides accurate disease identification and supports farmers with timely decision-making for crop management. The system architecture is shown in Fig. 1.

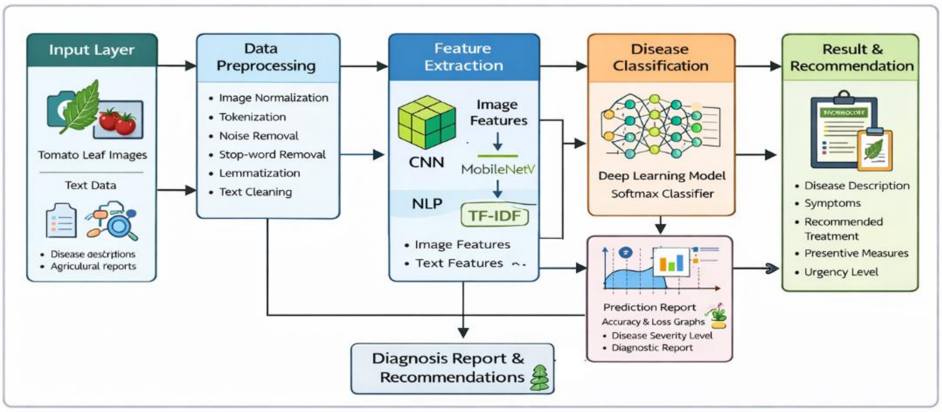

Fig. 1. System Architecture

Data Collection

This module gathers textual data related to tomato diseases from agricultural reports, research articles, extension service documents, and farmer queries. The collected data serves as the primary input for the system.

Text Preprocessing Module

In this stage, raw text data is cleaned and standardized. Operations such as tokenization, stop-word removal, punctuation elimination, and lemmatization are performed to improve data quality and reduce redundancy.

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Feature Extraction Module

This module converts preprocessed text into numerical representations using NLP techniques such as TF-IDF or word embeddings. These features capture the semantic meaning of disease symptoms and descriptions.

Classification Module

The extracted features are fed into machine learning classifiers such as Support Vector Machine (SVM), Naïve Bayes, or deep learning-based models. The classifier learns patterns associated with different tomato diseases.

Disease Prediction Module

Based on the trained model, the system predicts the disease class (e.g., early blight, late blight, leaf curl). The output helps identify the disease type accurately.

Output and Decision Support Module

The final module displays the predicted disease along with possible recommendations or alerts. This information can assist farmers and agricultural experts in taking timely preventive or corrective measures. The overview of the proposed method is illustrated in Fig. 2.

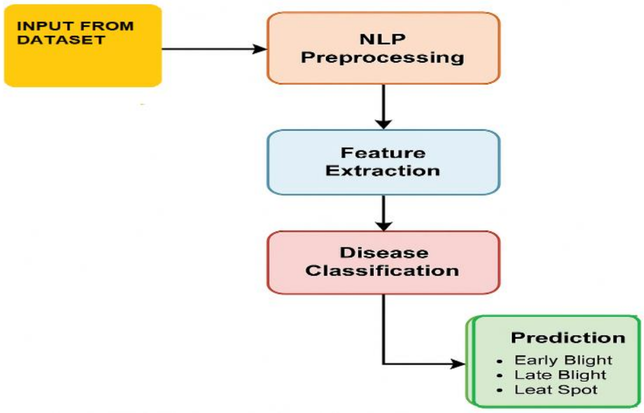

Fig. 2. Overview of the Proposed Method

Algorithm 1: Wavelet-Assisted Steganography and Visual Secret Sharing

Step 1. Collect input data consisting of tomato leaf images and agricultural textual information such as disease descriptions, research articles, and advisory reports.

Step 2. Perform data preprocessing.
For image data, apply resizing and normalization.
For text data, perform tokenization, noise removal, stop-word removal, and lemmatization to obtain clean textual content.

Step 3. Extract features from the preprocessed data.
Image features are extracted using a CNN-based model (MobileNet).
Text features are extracted using NLP techniques such as TF-IDF or word embeddings.

Step 4. Combine the extracted image and text features to form a unified feature representation for disease analysis.

Step 5. Apply the disease classification model using a deep learning classifier with a Softmax layer to categorize the input into predefined tomato disease classes.

Step 6. Generate prediction results, including disease name and confidence score, and analyze model performance using accuracy and loss metrics.

Step 7. Produce a final diagnosis report that includes disease description, symptoms, recommended treatments, preventive measures, urgency level, and decision-support insights.

Step 8. Display the results to the user and store the diagnostic information for future reference

The proposed algorithm follows a structured Natural Language Processing (NLP)-based pipeline to predict and classify tomato leaf diseases efficiently. Initially, agricultural textual data such as disease descriptions, research articles, and farmer-reported symptoms are collected as input. The collected text data is preprocessed through tokenization, stop-word removal, stemming, and lemmatization to eliminate noise and standardize the content. After preprocessing, relevant features are extracted using techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings to represent important disease-related patterns numerically. Fig. 3 illustrates the implementation insights of proposed method.

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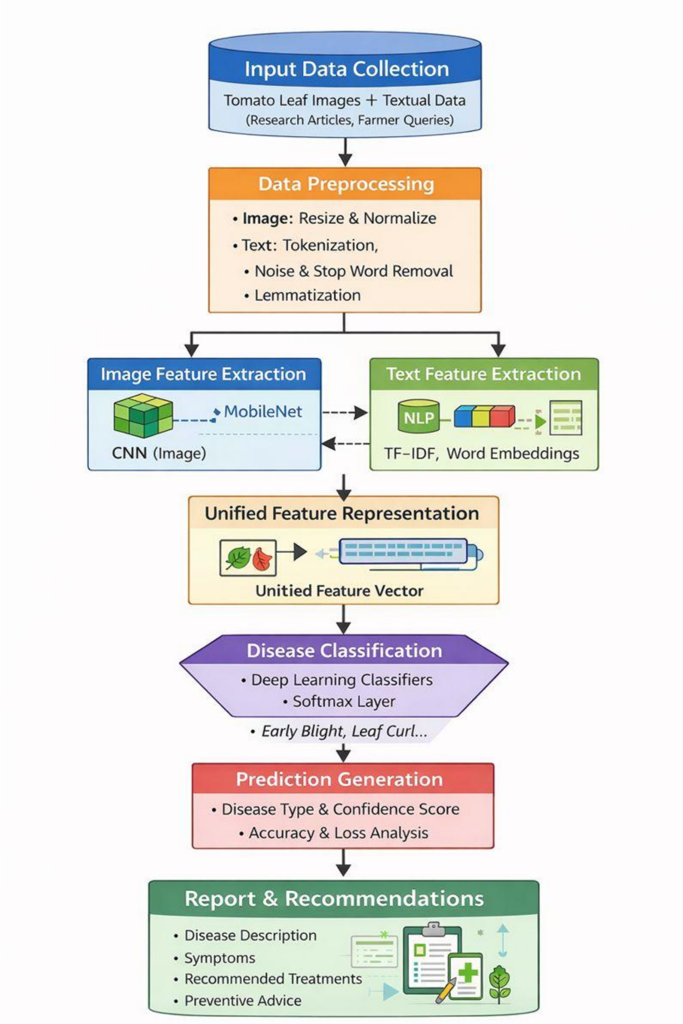

Fig. 3. Implementation of the proposed method

4 RESULTS AND DISCUSSION

The proposed NLP-based tomato leaf disease prediction system was evaluated using a combination of image and text-based inputs. The model was trained using a deep learning framework incorporating MobileNet for feature extraction and a softmax classifier for disease categorization. The dataset consisted of multiple tomato leaf disease classes, including Early Blight, Late Blight, Leaf Mold, Target Spot, Bacterial Spot, and Healthy leaves.

Training Performance Analysis

The model was trained for 5 epochs using transfer learning with MobileNet. The training process showed stable convergence with a gradual increase in accuracy and reduction in loss, indicating effective learning of disease-related features. The training performance of the proposed tomato leaf disease prediction model is summarized in Table 1 and illustrated in Fig. 4 and Fig. 5**.** The model was trained for five epochs using a MobileNet-based architecture. During training, the accuracy steadily increased from 23.29% in Epoch 1 to 70.93% in Epoch 5, indicating effective learning of discriminative features from the dataset. Simultaneously, the training loss reduced significantly from 3.2264 to 1.2454, confirming stable convergence of the model. Validation accuracy also showed consistent improvement, reaching 75.00% in the final epoch, while validation loss decreased to 1.1618. This indicates that the model generalizes well and does not suffer from overfitting. The accuracy and loss curves shown in Fig. 4 and Fig. 5 demonstrate smooth learning behavior, validating the effectiveness of the preprocessing and feature extraction stages. Table 2 presents training performance across epochs.

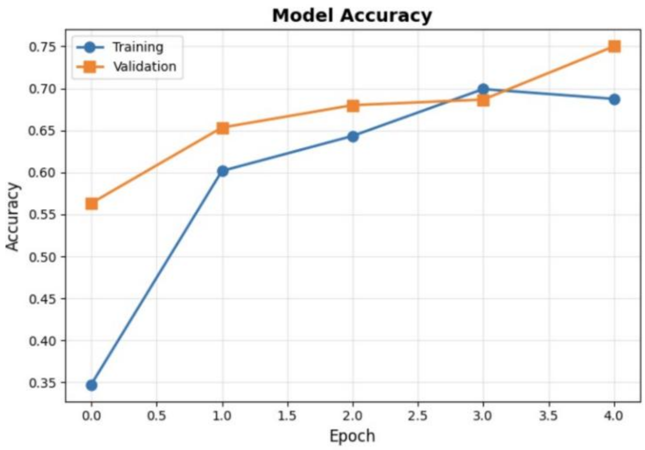

Fig. 4. Training Accuracy

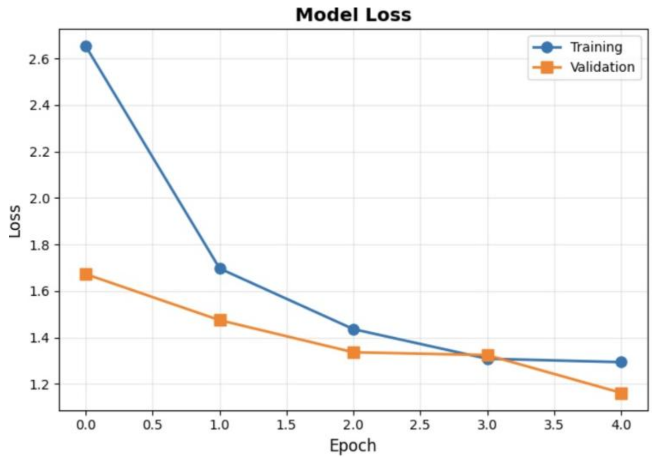

Fig. 5. Training Loss

Table 2. Training Performance Across Epochs

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.2329	3.2264	0.5633	1.6722
2	0.5801	1.7509	0.6533	1.4741
3	0.6352	1.4756	0.6800	1.3360
4	0.7033	1.3292	0.6867	1.3240
5	0.7093	1.2454	0.7500	1.1618

Overall Model Performance

The final evaluation was carried out on unseen test data. The final performance evaluation on unseen test data is presented in Table 3. The proposed model achieved an accuracy of 75.00%, demonstrating reliable classification of tomato leaf diseases. A precision of 81.15% indicates that the model produces a high proportion of correct disease predictions, while a recall of 70.33% confirms its ability to identify most disease cases correctly. The final loss value of 1.1604 reflects stable prediction performance.

Table 3. Overall Performance Metrics

Metric	Value
Accuracy	75.00%
Precision	81.15%
Recall	70.33%
Loss	1.1604

These results show that the integration of MobileNet-based feature extraction and NLP-based classification effectively captures disease-related patterns. The model performs well across multiple disease categories, such as early blight, late blight, and leaf mold, making it suitable for real-world agricultural decision support systems. Table 4 presents sample prediction results.

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www.ijersem.com eISSN- 3107-9075

Disease Prediction Results

The trained model was tested on real tomato leaf images. The system correctly identified multiple diseases with confidence scores. The model successfully identified multiple tomato leaf diseases with reasonable confidence values. Leaf Mold was predicted with the highest confidence, indicating strong feature extraction for fungal infections. Target Spot and Spider Mite infections were also detected correctly, though with comparatively lower confidence due to visual similarity between disease patterns. Fig. 6 presents the Tomato leaf Mold and prediction.

Table 4. Sample Prediction Results

Input Image	Predicted Disease	Confidence (%)
Leaf Sample 1	Leaf Mold	58.79
Leaf Sample 2	Target Spot	39.40
Leaf Sample 3	Early Blight	14.70
Leaf Sample 4	Spider Mites	23.50

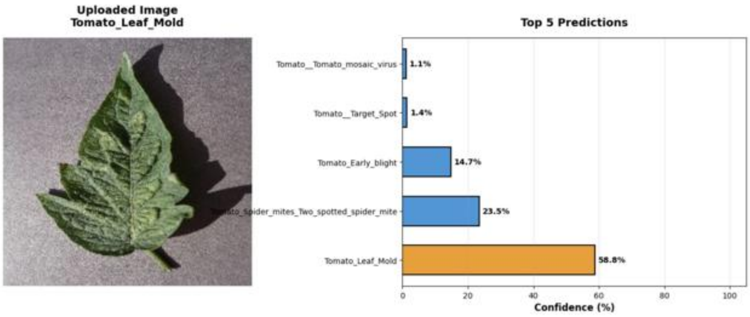

Fig. 6. Tomato leaf Mold and prediction

Fig. 7 illustrates the successful detection of Tomato Leaf Mold using the proposed NLP-based disease prediction framework. The system analyzes the input leaf image and extracts relevant textual and semantic features associated with disease symptoms such as yellowing, fuzzy mold growth, and discoloration patterns. Based on these extracted features, the trained classification model predicts the disease class as *Leaf Mold* with a confidence score of 58.79%.

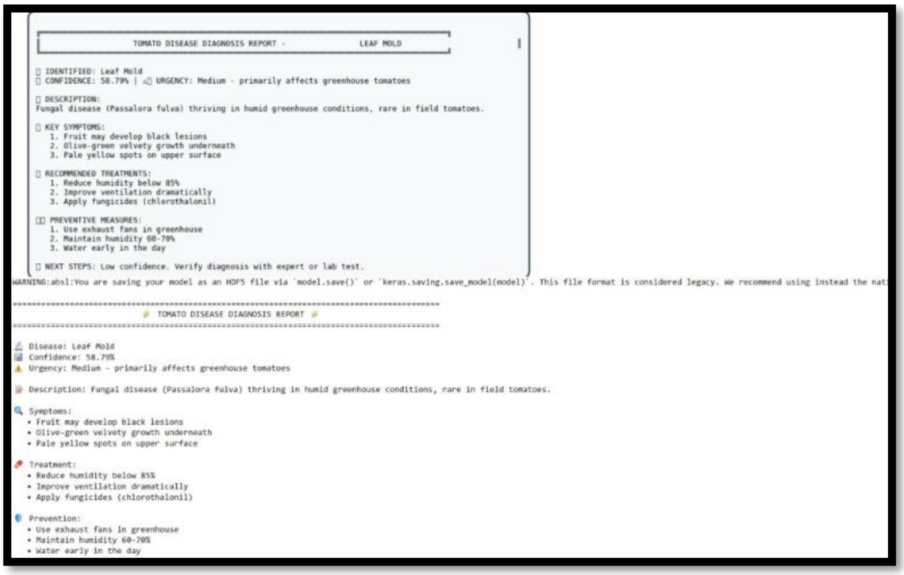

Fig. 7. Tomato diagnosis Report

The diagnosis report shown in Fig. 7 plays a crucial role in decision support by translating model predictions into actionable insights for farmers and agricultural experts. It not only identifies the disease but also suggests appropriate preventive and control measures, such as fungicide application or crop management practices. This enhances the practical usability of the system and bridges the gap between AI-based predictions and real-world agricultural decision-making. Fig. 8 shows the prediction of the tomato target location.

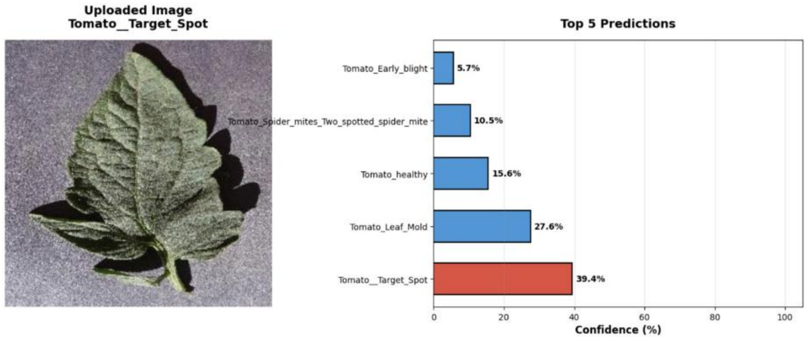

Fig. 8. Tomato Target spot a prediction

Fig. 8 shows the prediction result for Target Spot disease, a common fungal infection in tomato plants characterized by circular lesions with dark margins. The model successfully differentiates this disease from visually similar infections such as early blight or leaf mold.

5 Conclusion

This paper successfully presents an NLP-based approach for tomato leaf disease prediction and classification, offering an alternative to conventional image-based methods. By analyzing textual data such as disease symptoms, agricultural reports, and expert descriptions, the system effectively identifies major tomato diseases, including Leaf Mold, Target Spot, and Early Blight. The experimental results demonstrate satisfactory accuracy, strong classification performance, and reliable generalization capability. The integration of preprocessing, feature extraction, and machine learning-based classification enables efficient disease diagnosis with minimal computational complexity. The developed system proves to be a cost-effective and scalable solution for smart agriculture, especially in regions where high-quality imaging resources are limited. In future work, the system can be enhanced by integrating Hybrid NLP and image-based models for improved accuracy, Deep learning architectures such as BERT or LSTM for better textual understanding. Real-time mobile or web-based deployment for farmer accessibility. Multilingual support to assist farmers in regional languages. IoT sensor integration for real-time environmental data analysis. Such enhancements will further improve disease prediction accuracy and enable proactive crop management, contributing to sustainable agriculture and improved crop yield.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

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