JKPTB
Jurnal Keteknikan Pertanian Tropis dan Biosistem 12(3) 2024

Machine Learning-based Disease Classification in Tomato (*Solanum lycopersicum*) Plants

Klasifikasi Penyakit Berbasis Pembelajaran Mesin pada Tanaman Tomat (Solanum lycopersicum)

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ARTICLE HISTORY
Submitted September 6th, 2024
Accepted November 13th, 2024
Published December 31st, 2024

KEYWORDS
Detection; image processing; machine learning; plant diseases; tomato

KATA KUNCI
Deteksi; pembelajaran mesin; pemrosesan gambar; penyakit tanaman; tomat

ABSTRACT

In Bangladesh, tomato cultivation faces significant challenges due to its susceptibility to various microorganisms, parasites, and bacterial infections. Typically, the early symptoms of these diseases first appear in roots and leaves, complicating timely detection. This study addresses the challenge of timely and accurate detection of diseases in tomato plants, crucial for effective plant protection management. Conventional manual inspection methods are time-consuming and subjective, resulting in delays in implementing necessary protection measures. Therefore, an image processing technique and machine learning algorithms were used for rapid and robust detection of diseases in tomato plant leaves, aiming to streamline the detection process for chemical application responses. A dataset containing 250 images of tomato plant leaves were captured under varying light intensities, eye-level angles, and distances. Image augmentation techniques were applied to increase the dataset, resulting in a total of 529 images. These images were converted to LAB color images and then OTSU algorithm was used to segment leaf images and estimate the percentage of affected diseased areas. Various textural features were also extracted from segmented leaf images to create a training dataset. Machine learning algorithms, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and decision trees, were trained and evaluated using this dataset to classify images as healthy or diseased. The Quadratic SVM algorithm provided the highest test accuracy of 97.7% for the dataset. This nondestructive processing holds immense promise for improving disease detection efficiency and reducing losses in tomato production, both locally in Bangladesh and globally.

ABSTRAK

Di Bangladesh, budidaya tomat menghadapi tantangan yang signifikan karena kerentanannya terhadap berbagai mikroorganisme, parasit, dan infeksi bakteri.

doi https://doi.org/10.21776/ub.jkptb.2024.012.03.01

Biasanya, gejala awal penyakit-penyakit ini pertama kali muncul di akar dan daun, sehingga menyulitkan deteksi tepat waktu. Penelitian ini membahas tantangan deteksi penyakit yang tepat waktu dan akurat pada tanaman tomat, yang sangat penting untuk manajemen perlindungan tanaman yang efektif. Metode inspeksi manual konvensional memakan waktu dan subjektif, sehingga mengakibatkan penundaan dalam menerapkan tindakan perlindungan yang diperlukan. Oleh karena itu, teknik pemrosesan gambar dan algoritma pembelajaran mesin digunakan untuk mendeteksi penyakit pada daun tanaman tomat dengan cepat dan kuat, yang bertujuan untuk merampingkan proses deteksi untuk respons aplikasi kimia. Sebuah dataset yang berisi 250 gambar daun tanaman tomat diambil di bawah berbagai intensitas cahaya, sudut pandang, dan jarak. Teknik augmentasi gambar diterapkan untuk meningkatkan dataset, menghasilkan total 529 gambar. Gambar-gambar ini diubah menjadi gambar berwarna LAB dan kemudian algoritma OTSU digunakan untuk mensegmentasi gambar daun dan memperkirakan persentase area yang terkena penyakit. Berbagai fitur tekstur juga diekstraksi dari gambar daun yang telah disegmentasi untuk membuat dataset pelatihan. Algoritma pembelajaran mesin, termasuk Support Vector Machines (SVM), K-Nearest Neighbors (KNN), dan pohon keputusan, dilatih dan dievaluasi dengan menggunakan set data ini untuk mengklasifikasikan gambar sebagai gambar yang sehat atau sakit. Algoritma Quadratic SVM memberikan akurasi pengujian tertinggi sebesar 97.7% untuk dataset. Pemrosesan nondestruktif ini sangat menjanjikan untuk meningkatkan efisiensi pendeteksian penyakit dan mengurangi kerugian dalam produksi tomat, baik secara lokal di Bangladesh maupun global.

doi https://doi.org/10.21776/ub.jkptb.2024.012.03.01

1. Introduction

With the global population projected to reach 9.6 billion by 2050, ensuring global food security becomes increasingly critical. However, in-field crop losses pose a significant threat, expected to affect a third of total agricultural production by that time [1]. Plant disease stands out as a major barrier to agricultural commodities, resulting in reduced supply and performance degradation. Plant pathogens, such as fungi, bacteria, and viruses, are the primary causes of plant diseases. Over 454 diseases have been recorded in around 100 cultivated crops so far, emphasizing the issue’s breadth [2]. These pathogens and diseases can cause substantial reductions in production, directly impacting public nutrition.

Cash crop monitoring is essential for optimizing production and efficiency. Among crops, tomatoes hold significant importance worldwide. Tomatoes are rich sources of natural antioxidants and are widely consumed in various forms in everyday diets worldwide. However, their availability can be limited during certain seasons. In 2015, tomatoes were grown on 5.05 million hectares of land globally, yielding approximately about 187 million metric tons [3], figures notably lag behind those observed in other major tomato growing regions studied by [4]. Several factors contribute to this production disparity, including bacteria, fungi, viruses, and nematodes, significantly challenging tomato production. Tomatoes are extensively cultivated in Bangladesh, contributing significantly to agricultural production with an annual yield exceeding 380,000 tons across approximately 27,342 hectares of land. Despite this, Bangladeshi tomato farmers face numerous obstacles throughout the cultivation process. Among these challenges, combating diseases affecting tomato plant leaves is particularly prominent [5]. Healthy tomato plants typically exhibit uniformly green color leaves [6]. However, the onset of disease symptoms on the tomato leaves during growth [7].The current method for detecting tomato plant diseases heavily relies on visual evaluation by experts, which can be both costly and impractical, especially on large-scale farms. Moreover, in developing countries like Bangladesh, farmers lack access to adequate facilities or may not possess the knowledge to promptly notify experts of potential issues. Human-based quantification and identification of diseases are prone to inefficiency and errors focusing the urgent need for a convenient, affordable, and precise disease detection method in tomato plant leaf.

Computer vision technologies have emerged as promising tools for agricultural applications, including plant phenotyping, disease detection, and identification [7-9]. Over the years, numerous research initiatives on agricultural product processing have been initiated, with several techniques developed to identify and characterize leaf defects [9-10]. Recent literature highlights the widespread and efficient use of image processing techniques for disease detection in agriculture [11-14]. For instance, neural networks have been used to recognize leaf diseases [15], employing Prewitt edge detection and thinning function to obtain back-propagation algorithms. Boundary detection and spot detection techniques were used for extracting leaf characteristics [14]. The introduction of the 'YCbCr' color space technology' has enabled the segmentation of disease spots [16]. Grayscale image processing techniques, such as histogram equalization and the co-occurrence matrix computation, was proposed by Bashir [17] for the detection of diseases in Malus Domestica leaves. In [18], Singh and Misra described a four-step processing system involving color transformation, masking of green pixels, removal using a specific threshold value, and segmentation for disease detection.

In a critical window of time, the timely identification of specific diseases is imperative to prevent their rapid spread, minimize losses from pest or disease infestation, and optimize yield. A monitoring system needs to be rapid and robust to achieve this. Precise classification of diseased and healthy plants through leaves is necessary and identification of infected areas allows targeted chemical application at varying rates, fostering cost-effectiveness and environmental sustainability. The present study attempts to classify tomato leaf images as healthy or diseased using minimal image pre-processing and using different machine learning models.

2. Materials and Methods

2.1 Image Acquisition

The leaf images were acquired using a digital camera (Resolution 13 MP, aperture f/2.2, and ide-angle lens 28 mm, Xiaomi Corporation, Beijing, China). These images were captured at a resolution of 1080×2340 pixels. The tomato leaf images were collected from plants in August 2019 at the Sylhet Agricultural University research plot, located at coordinates 24°54'40"N, 91°54'08"E in Bangladesh. The images were captured carefully using a white board to exclude complex backgrounds, ensuring clarity in the visual data. Subsequently, the captured images were cropped to include only the leaf portion and resized to dimensions of 300×300 pixels for avoiding unnecessary computing requirement in processing step. In the disease identification process, the leaves of tomato plants are systematically processed to locate the affected areas and identify classifiers for disease detection. This process is illustrated in **Figure 1**.

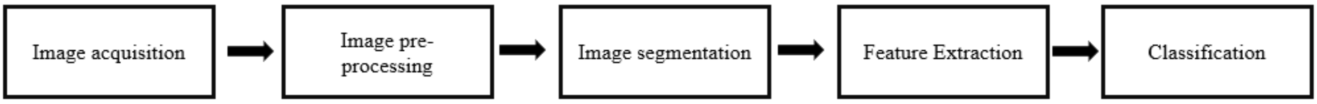

Figure 1. Flowchart illustrating the image processing pipeline for identifying diseases in tomato leaves

The dataset comprised a total of 250 images. **Figure 2** shows some images of tomato leaves from the database, with some of the images depicting healthy leaves and remainder showing affected regions which may represent diseased plant. To enhance the dataset’s robustness and diversity for training machine learning models, geometric transformations such as rotation and scaling, along with color jittering and horizontal flipping, were applied for data augmentation to increase the dataset volume. This augmentation process resulted in a total of 529 images.

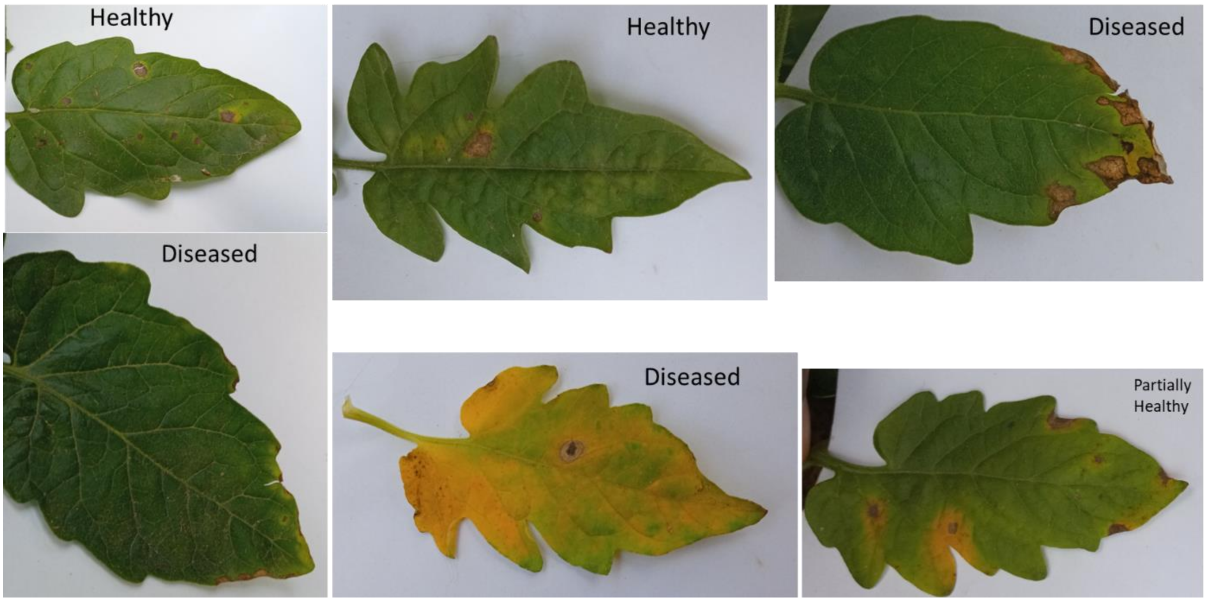

Figure 2. Sample of tomato leaf images database for processing

2.2 Image Segmentation

An Intel® Core™ i9-10885H CPU @ 2.40GHz, operating on a 64-bit operating system with an x64-based processor, was used for image processing tasks. MATLAB R2023b (The MathWorks, Inc., USA) served as the primary software for image processing. In this study, various preprocessing techniques were employed to optimize images of diseased tomato leaves.

RGB images were converted to the LAB color space to separate luminosity and chromaticity components, facilitating the extraction of color-based features related to disease. Green or near-green pixels representing healthy regions were removed as shown in **Figure 3**, and Otsu’s method was applied to segment diseased areas from the background. Otsu’s thresholding was specifically applied to the L channel, with a single threshold value for gray and white pixels after removing healthy regions based on A and B channel values. This thresholding step was iterated to progressively refine segmentation accuracy.

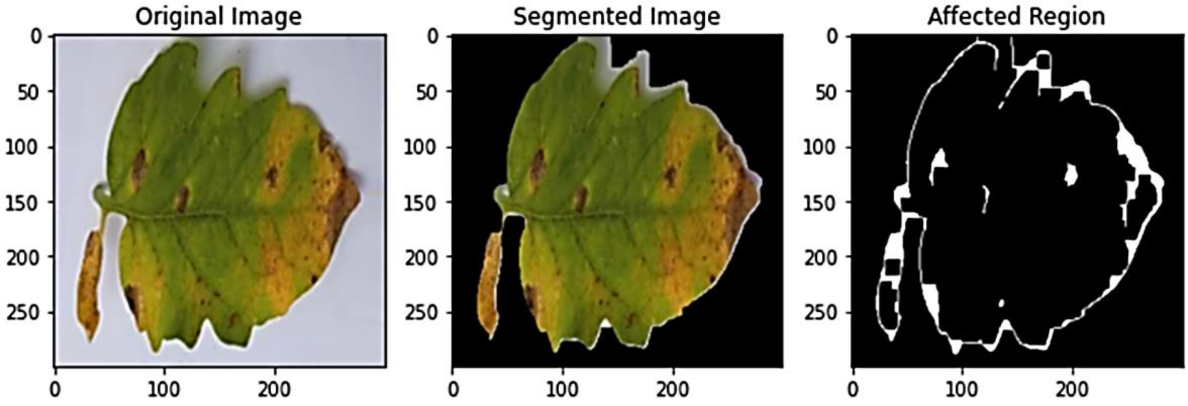

Figure 3. Steps followed to segment the leaf image and extract affected region

2.3 Feature Extraction

The region of interest (ROI) was precisely defined as the leaf portion, excluding the background. The affected region was identified by binarizing the segmented image and counting nonzero pixels. Then the percentage of affected region was calculated using **Equation 1.**

$$\textbf{Affected region}\ (\%) = \frac{\textbf{Area of total affected region}\ (\textbf{pixels})}{\textbf{Segmented Leaf image from background}\ (\textbf{pixels})} \times \mathbf{100} \qquad (1)$$

To extract features from the ROI of each image, the gray-level co-occurrence matrix (GLCM) method was used. The GLCM measures the frequency of co-occurring gray levels at a specified offset between neighboring pixels in an image. Four offsets in different directions and distances were considered, including vertical, lateral, two diagonals, and four distances.

Affected areas for all images were calculated using color thresholding. Statistical texture features extracted from the GLCM included contrast, correlation, energy, and homogeneity. These GLCM-based texture features were constructed from the grayscale image to analyze spatial relationships between pixel intensities. These features captured textural properties such as local intensity variations, linear dependence of pixel intensities, overall intensity content, and homogeneity of pixel distributions. In addition, numerical indicators such as mean, standard deviation, entropy, skewness, and energy were calculated from the histograms of the color planes. The histogram was created using the grayscale image obtained by converting the segmented image to grayscale using the “rgb2gray” function. These features provided insights into the overall intensity distribution and complexity of the leaf region.

2.4 Model Training and Performance

The dataset containing both healthy and unhealthy tomato leaf images was used to extract features, which were then trained with different machine learning algorithms. From this dataset (total of 529 images where 217 images are from healthy leaves and 312 images from diseased leaves), 75% of data was used for training and 25% of it was used for testing. The algorithms included discriminant analysis, native bayes classifiers, SVM, Nearest neighbor classifier and decision trees. During training those models, the predictor variables were contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, skewness, energy and the percentage of affected area in the leaf. The response variable was the image class (healthy or diseased).

To assess the performance of these classifiers, standard performance metrics such as accuracy and confusion matrix were used. Since the images were already labelled as healthy or diseased, the formulation for correctly classified instances was calculated using **Equation 2**. This formulation considers the model's predictions of true positives, true negatives, false positives, and false negatives, ultimately computing the proportion of correctly classified instances out of the total number of instances. The study attempted to use textural features extracted from the input dataset to accurately classify tomato leaves as healthy or unhealthy, using various classification algorithms.

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}} \times 100\% \qquad (2)$$

Where, TP = true positive, represents an outcome where the model accurately predicts the positive class; TN=true negative, represents an outcome where the model accurately predicts the negative class; FP=false positive, represents an outcome where the model inaccurately predicts the positive class; FN=false negative, represents an outcome where the model inaccurately predicts the negative class.

3. Results and Discussion

3.1 Extracted Features

The feature extraction process involved extracting ten different features from the selected leaf area. These features included affected percentage, mean, standard deviation, entropy, RMS, variance, kurtosis, skewness, contrast, and energy. The values of these features were calculated and stored on an Excel sheet, creating a training database. The summary statistics for each feature are presented in **Table 1**.

Table 1. Summary statistics of extracted features from leaf images

		Affected area %	**Mean**	**Std. Dev.**	**Entropy**	**RMS**	**Variance**	**Kurtosis**	**Skewness**	**Contrast**	**Energy**
Healthy n=217	Min.	2.99	17.43	26.24	324.80	5.70	688.40	1.30	-0.68	73.00	0.02
	1st Qu.	6.86	30.06	32.57	877.40	6.96	1061.10	2.72	0.22	212.30	0.15
	Median	8.45	30.06	33.79	1011.70	7.45	1141.70	3.48	0.56	251.70	0.22
	Mean	**8.70**	**30.06**	**41.29**	**1052.70**	**7.53**	**1845.80**	**3.48**	**0.58**	**265.00**	**0.23**
	3rd Qu.	10.74	30.06	45.03	1259.10	8.10	2027.40	4.21	0.93	326.10	0.29
	Max.	16.56	30.06	65.54	1737.40	9.96	4295.70	7.76	1.86	457.40	0.50
Diseased n= 312	Min.	1.47	15.94	24.24	404.90	4.29	587.60	1.39	-1.47	90.61	0.01
	1st Qu.	5.78	36.77	41.30	775.70	6.93	1705.70	1.75	-0.07	189.52	0.13
	Median	8.89	45.13	45.86	910.00	7.66	2103.60	1.99	0.27	220.90	0.23
	Mean	**12.13**	**47.58**	**45.37**	**954.60**	**7.60**	**2105.60**	**2.23**	**0.29**	**235.91**	**0.24**
	3rd Qu.	11.96	54.77	50.36	1074.70	8.38	2536.30	2.45	0.68	257.28	0.32
	Max.	100.00	110.81	61.33	2828.60	10.15	3761.20	6.07	1.77	711.69	0.63

In this table, healthy tomato leaves (n=217) showed the mean affected area of 8.70% whereas the diseased leaves (n=312) showed 12.13%.

3.2 Model Performance

To evaluate the accuracy of the proposed models, 25% of the dataset was used for testing purposes. The response variable represented the class variable for leaves distinguishing between healthy and diseased. K-fold cross validation (k-fold=7) was used to evaluate the machine learning models, including SVM, discriminant analysis, trees, and KNN, were tested to determine the most suitable model for the dataset. The accuracy results for these models are summarized in **Table 3**.

Among the models tested, the Quadratic SVM model achieved the highest accuracy rates of 98% for validation and 97.7% for the test dataset. This model demonstrated excellent performance in classifying the leaf diseases.

Moreover, the medium Gaussian SVM, Cubic SVM, Weighted KNN, Fine KNN, and Linear SVM models showed accuracy rates above 95% for both validation and test results. Conversely, the Coarse KNN showed the lowest accuracy in predicting leaf disease, with validation accuracy at 74.3% and test accuracy at 76.5%.

Table 2. Accuracy result of machine learning models

Model	Validation Accuracy (%)	Test Accuracy (%)
Quadratic SVM	98.0	97.7
Medium Gaussian SVM	97.0	97.0
Cubic SVM	96.7	97.0
Weighted KNN	96.7	95.5
Fine KNN	96	95.5
Linear SVM	95.3	95.5
Fine Gaussian SVM	94.5	93.9
Fine tree	89.9	90.9
Gaussian Native Bayes	86.6	87.9
Coarse KNN	74.3	76.5

The confusion matrix and ROC (receiver operating characteristic) curve shown in **Figure 4** further illustrate the performance of the models, revealing high sensitivity and specificity values. The ROC curve, which evaluates the performance of a classification model across all classification thresholds, shows an impressive AUC (area under the curve) of 0.99 for leaf categories. Upon analyzing the confusion matrix, it is apparent that 100% of diseased and 94.4% of healthy leaves were correctly classified, while a small portion (5.6%) of the healthy leaves was misclassified as diseased. The results from this study indicate that the proposed approach in successfully classifying tomato leaf images accurately for healthy and unhealthy category. Specifically, the Quadratic SVM model proved the most accurate for this dataset. To ensure the reliability of the results, cross-checking procedures were implemented. These results provide valuable insights into the performance of the algorithm, serving as a foundation for potential improvements and applications in plant disease detection and agricultural management.

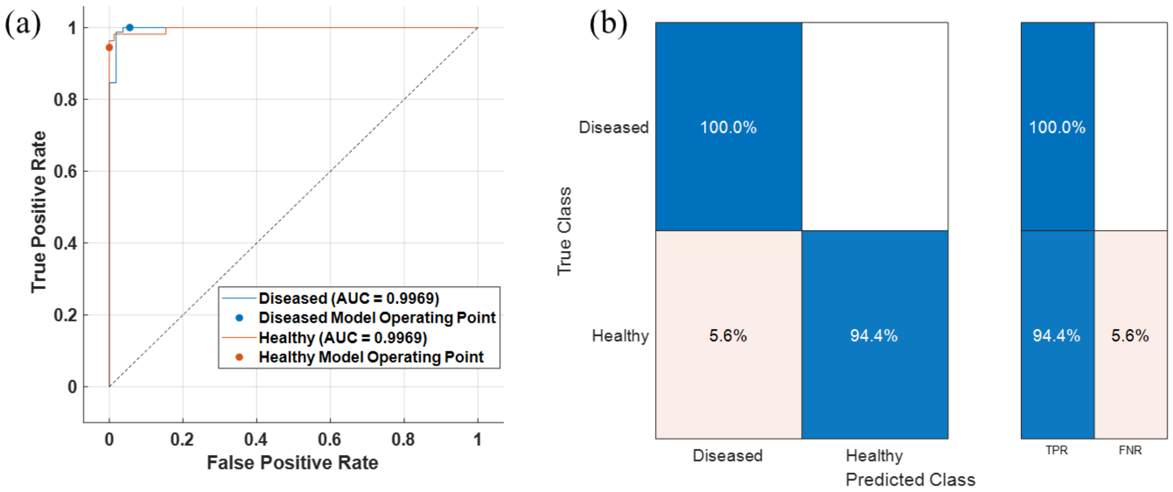

Figure 4. ROC curve and confusion matrix

(Note: (a) ROC curve is plotted to graphically represent the connection between clinical sensitivity and specificity for every possible cut-off. For the Quadratic SVM, the value of AUC was found to be 1.00. (b) The confusion matrix for diseased and healthy leaf classification, TPR=True positive rate, FNR= False negative rate)

The main objective of this study is to accurately identify diseased areas on tomato plant leaves and classify them as either diseased or healthy based on leaf features. We employed image acquisition and preprocessing techniques to enhance image quality and reduce noise, mainly focusing on segmentation. The K-means clustering algorithm was utilized for segmentation within LAB color space images, extracting features from each segmented image to represent the actual leaf region without background. Additionally, the algorithm quantified the total affected area of the leaf, a crucial feature for subsequent analysis. All extracted features, including the percentage of affected leaf area, served as predictor variables for training various models. It would be beneficial to include more images covering different stages of tomato plant growth, diverse lighting conditions, and backgrounds to enhance generalization. Prioritizing certain features and introducing additional ones during model training could also improve performance.

Overall, the results demonstrate the effectiveness of the developed leaf disease classification system. The high accuracy achieved by the model confirms the potential of the proposed approach for automated leaf disease detection and diagnosis. In the context of Bangladesh, this approach could serve as a valuable tool for developing an automated crop monitoring system.

4. Conclusions

In this study, techniques for detecting diseases in tomato plant leaves disease were developed and evaluated. A dataset comprising 529 digital images of both diseased and healthy tomato leaves showing visible affected regions was used for this purpose. Image processing techniques, and machine learning algorithms were used to classify diseased and healthy leaves accurately, and effectively. The image processing algorithms allowed feature extraction from each image, enabling the identification of affected leaf areas. Using the extracted dataset, various machine learning classifiers were trained and evaluated to distinguish between diseased and healthy leaves. The Quadratic SVM algorithm was shown the highest accuracy in predicting whether the leaves were diseased or not. The application of these techniques at an early stage enables expedited disease detection, allowing timely intervention and potential mitigation of crop losses. To achieve optimum detection accuracy across various plant species, further exploration of testing materials, analysis methods, and image processing techniques can be explored.

Acknowledgements

This work was supported by the University Grants Commission (UGC), Bangladesh Project No. Agri (Crop-30)/2018. The authors would like to appreciate the logistic supports or this study from the Department of Farm Power and Machinery, Sylhet Agricultural University.

References

[1] E. Oerke, “Crop losses to pests,” *The Journal of Agricultural Science*, vol. 144, no. 1, pp. 31–43, Feb. 2006, doi: 10.1017/S0021859605005708.

[2] M. T. Hossain, S. M. M. Hossain, M. A. Bakr, A. K. M. Matiar Rahman, and S. N. Uddin, “Survey on major diseases of vegetable and fruit crops in Chittagong region,” *Bangladesh Journal of Agricultural Research*, vol. 35, no. 3, pp. 423–429, Jan. 2010, doi: 10.3329/BJAR.V35I3.6449.

[3] “Worldwide (total fresh) tomato production exceeds 187 million tonnes in 2020 - Tomato News.” Accessed: Apr. 04, 2024. [Online]. Available: https://www.tomatonews.com/en/worldwide-total-fresh-tomato-production-exceeds-187-million-tonnes-in-2020_2_1565.html

[4] A. Biswas, S. Chandra Dey, and S. Sarker, “Growth and yield performances of tomato genotypes during winter season at eastern surma kushiyara floodplain of Bangladesh,” *J. Sylhet Agril. Univ.*, vol. 4, no. 1, 2017.

[5] Md. A. A. Mamun, D. Z. Karim, S. N. Pinku, and T. A. Bushra, “TLNet: A Deep CNN model for Prediction of tomato Leaf Diseases,” in *2020 23rd International Conference on Computer and Information Technology (ICCIT)*, DHAKA, Bangladesh: IEEE, Dec. 2020, pp. 1–6. doi: 10.1109/ICCIT51783.2020.9392664.

[6] P. S. Gilmour, “How to select tools for rnicrocontroller software,” *IEEE Spectrum*, vol. 28, no. 2, pp. 37–39, 1991, doi: 10.1109/6.100908.

[7] U. Mokhtar *et al.*, “SVM-Based detection of tomato leaves diseases,” *Advances in Intelligent Systems and Computing*, vol. 323, pp. 641–652, 2015, doi: 10.1007/978-3-319-11310-4_55.

[8] Z. Li, R. Guo, M. Li, Y. Chen, and G. Li, “A review of computer vision technologies for plant phenotyping,” *Computers and Electronics in Agriculture*, vol. 176, p. 105672, Sep. 2020, doi: 10.1016/J.COMPAG.2020.105672.

[9] M. A. Momin, M. T. Rahman, M. S. Sultana, C. Igathinathane, A. T. M. Ziauddin, and T. E. Grift, “Geometry-based mass grading of mango fruits using image processing,” *Information Processing in Agriculture*, vol. 4, no. 2, pp. 150–160, 2017, doi: 10.1016/j.inpa.2017.03.003.

[10] T. Rahman *et al.*, “Characterization of tea (Camellia sinensis) granules for quality grading using computer vision system,” *Journal of Agriculture and Food Research*, vol. 6, p. 100210, 2021, doi: 10.1016/j.jafr.2021.100210.

[11] J. Gui, L. Hao, Q. Zhang, and X. Bao, “A new method for soybean leaf disease detection based on modified salient regions,” *International Journal of Multimedia and Ubiquitous Engineering*, vol. 10, no. 6, pp. 45–52, 2015, doi: 10.14257/ijmue.2015.10.6.06.

[12] N. Chamara, G. Bai, and Y. Ge, “AICropCAM: Deploying classification, segmentation, detection, and counting deep-learning models for crop monitoring on the edge,” *Computers and Electronics in Agriculture*, vol. 215, p. 108420, Dec. 2023, doi: 10.1016/j.compag.2023.108420.

[13] M. S. P. Babu and B. S. Rao, “Leaves Recognition Using Back Propagation Neural Network-Advice for Pest & Disease Control on Crops . Leaves Recognition Using Back Propagation Neural Network-Advice for Pest & Disease Control on Crops . 3 . Requirement Specification 4 . Tools Techniques,” *Prospectiva*, vol. 7, no. Enero-Junio de 2009, pp. 67–73, 2007.

[14] S. Phadikar and J. Sil, “Rice disease identification using pattern recognition techniques,” *Proceedings of 11th International Conference on Computer and Information Technology, ICCIT 2008*, no. Iccit, pp. 420–423, 2008, doi: 10.1109/ICCITECHN.2008.4803079.

[15] M. S. P. Babu and B. S. Rao, “Leaves Recognition Using Back Propagation Neural Network-Advice for Pest & Disease Control on Crops . Leaves Recognition Using Back Propagation Neural Network-Advice for Pest & Disease Control on Crops . 3 . Requirement Specification 4 . Tools Techniques,” *Prospectiva*, vol. 7, no. Enero-Junio de 2009, pp. 67–73, 2007.

[16] S. Kai, L. Zhikun, S. Hang, and G. Chunhong, “A Research of Maize Disease Image Recognition of Corn Based on BP Networks,” in *2011 Third International Conference on Measuring Technology and Mechatronics Automation*, Shanghai, China: IEEE, Jan. 2011, pp. 246–249. doi: 10.1109/ICMTMA.2011.66.

[17] S. Bashir, “Remote Area Plant Disease Detection Using Image Processing,” *IOSR Journal of Electronics and Communication Engineering*, vol. 2, no. 6, pp. 31–34, 2012, doi: 10.9790/2834-0263134.

[18] V. Singh and A. K. Misra, “Detection of plant leaf diseases using image segmentation and soft computing techniques,” *Information Processing in Agriculture*, vol. 4, no. 1, pp. 41–49, 2017, doi: 10.1016/j.inpa.2016.10.005.