Early Detection of Late Blight Tomato Disease using Histogram Oriented Gradient based Support Vector Machine

M. Ishaq (drmishaq@aup.edu.pk)*, M. Waqas (muhammadwaqas2k18@gmail.com)

Abstract—The tomato is one of the most important fruits on earth. It is rich in nutrients, has the best taste, and has other good health benefits. It plays an important and useful role in the agricultural production of any country. An increase in tomato diseases causes an increase in the import of tomatoes, which affects the economy of the country. This research improved the dataset with an increase in images from the field (the Plant Village dataset) and proposed a hybrid algorithm composed of support vector machines (SVM) and histogram-oriented gradients (HOG) for real-time detection of late blight tomato disease. The use of the proposed hybrid algorithm in the smart agriculture field for the detection of late blight on tomatoes would increase and protect its production. To enhance the image dataset through the inclusion of early-affected and late-blight tomato leaves. To propose a HOG-based SVM model for early detection of late blight tomato leaf disease. To check the performance of the proposed model in terms of MSE, accuracy, precision, and recall as compared to Decision Tree and KNN. The integration of advanced technology in agriculture has the potential to revolutionize the industry, making it more efficient, sustainable, and profitable. This research work on the early detection of tomato diseases contributes to the growing importance of smart farming, the need for climate-smart agriculture, the rising need to more efficiently utilize natural resources, and the demand for higher crop yields. The proposed hybrid algorithm of SVM and HOG has significant potential for the early detection of late blight disease in tomato plants. The performance of the proposed model against decision tree and KNN algorithms and the results may assist in selecting the best algorithm for future applications. The research work can help farmers make data-driven decisions to optimize crop yield and quality while also reducing the environmental impact of farming practices.

Keywords—HOG,KNN, MSE, SVM

I. INTRODUCTION

Tomatoes are the most commonly cultivated crop all over the world. The annual estimated production in recent years has been over 100 million metric tons. For production to increase, we need smart agricultural techniques. There are five of the most common tomato diseases. These diseases have the worst effect on tomato production. A fungus causes late blight, which is one of the common diseases that reduce production. Early detection of such dangerous microbes enables us to spray the required pesticides and ensure crop protection. Due to climate change, the numbers of pollinators are decreasing (Bir et al., 2020). Some insects that help in pollination may possibly attack leafy parts of the plants and destroy crops.

In smart agriculture, there are improved computational methods that can help us detect pathogens and parasites in their early stages (Hasan et al., 2019). Smart farming is the concept that helps the farming industry with the infrastructure it requires to utilize modern technology for automating, tracking, and analyzing activities, such as big data, the cloud, and the internet of things (IOT). Smart farming, also referred to as precision agriculture, is software-managed and sensor-monitored (Elhassouny&Smarandache,

2019). The need for climate-smart agriculture, the rising need to more efficiently utilize natural resources and the demand for higher crop yields, the growing use and sophistication of information and communication technology, and the expanding global population all contribute to the growing importance of smart farming.

Machine learning is a branch of artificial intelligence that enables computer systems to learn from data and apply that learning to predict. It has proven to be a valuable tool in various domains, including image recognition, natural language processing, robotics, and data analytics. The fundamental principle behind machine learning is to enable the computer system to learn from past experiences and apply that learning to future situations. The process of machine learning involves feeding large amounts of data into an algorithm, which then uses statistical methods to identify patterns and relationships within the data.

The research uses Support Vector Machine (SVM) and Histogram Oriented Gradient (HOG), the best computational algorithms, to detect pathogens in tomato leaf disease (Zhang et al., 2018). Dalal&Triggs (2005) use HOG to detect human techniques used to identify different diseases in tomato leaf disease. The use of technologies like smart agriculture refers to the use of the Internet of Things, sensors, navigational aids, and artificial intelligence on your farm. The ultimate purpose is to increase the use of human workers while raising crop yield and quality (Kumar &Vani, 2019).

The histogram of oriented gradients (HOG) technique detects edges and corners in an image by analyzing the gradient of the image intensity (Tyagi, 2021). HOG generates a histogram of the directions of the gradients, which is used as a feature vector (Tyagi, 2021).

The pathogen Phytophthorainfestans is the source of the fungal disease known as late blight that affects tomato plants. It can result in severe crop losses and is a critical issue in warm, humid settings. Gray spots on the leaves, stems, fruit, and flowers constitute the symptoms. A red ring may appear around the white center of certain diseases. As the disease spreads quickly in warm, moist environments, it's crucial to take precautions to lower the risk of infection. Infected plants should be removed, crops rotated, and fungicides should be used. This research uses a Support Vector Machine (SVM) classifier and a Histogram of Oriented Gradients (HOG) feature descriptor to identify the late blight tomato disease. The dataset used includes 1900 images of late blight disease in tomato leaves obtained from the field and the Kaggle Plant Village dataset.

The research methodology includes dataset preparation, feature extraction using HOG descriptors, and training of an SVM classifier. The model's performance is evaluated using accuracy, precision, recall, and mean square error (MSE). Data augmentation techniques such as flipping and rotation are applied to enhance the dataset. The proposed HOG-based SVM algorithm is implemented in Jupyter Notebook using Python. The dataset is split into training (70%) and testing

(30%) subsets. This research can be helpful for real-time detection of late blight tomato disease and for crop protection and productivity in tomato farming.

A. Research Background

Tomatoes are a widely cultivated crop, with an annual production of over 100 million metric tons. However, tomato production is severely impacted by five common diseases, including the fungus-caused late blight. Early detection of these diseases is crucial for crop protection and increased production. Climate change and reduced pollinator populations can also harm tomato crops. Smart agriculture techniques and improved computational methods can aid in the early detection of pathogens and parasites. Smart farming, which utilizes cutting-edge technology for automating, tracking, and analyzing activities, is becoming increasingly important due to the need for climate-smart agriculture, efficient resource utilization, higher crop yields, and the expanding global population.

The pathogen Phytophthorainfestans is the source of the fungal disease known as late blight that affects tomato plants. It can result in severe crop losses and is a critical issue in warm, humid settings. Gray spots on the leaves, stems, fruit, and flowers constitute the symptoms. A red ring may appear around the white center of certain diseases. As the disease spreads quickly in warm, moist environments, it's crucial to take precautions to lower the risk of infection. Infected plants should be removed, crops rotated, and fungicides should be used. Figure1 shows the symptoms of late blight tomato disease. They usually begin with dark green to brownish-black water-soaked areas on the leaves, which may later become yellow or brown.



Figure 1: Late Blight Tomato Leaves

In the field of smart agriculture, using machine learning algorithms for early tomato disease detection is becoming more vital. The use of these technologies can help farmers detect diseases at an early stage and take the necessary actions to prevent crop loss. In this study, support vector machine (SVM) and histogram-oriented gradient (HOG) algorithms are used to detect late blight disease in tomato plants. The concept of smart farming has gained traction in recent years, as it provides farmers with the ability to automate and monitor their agricultural activities using sensors, the cloud, and the Internet of Things (IOT). This research can help farmers make data-driven decisions to optimize crop yield and quality while also reducing the environmental impact of farming practices. The impact of climate change has also made it necessary to adopt climatesmart agriculture practices, which promote sustainable farming methods and reduce the carbon footprint of farming. The integration of advanced technology in agriculture has the potential to revolutionize the industry, making it more efficient, sustainable, and profitable.

B. Motivation

Being an agricultural country, we are well aware of the damage caused by late blight disease in tomatoes. This disease affects the balance of supply and demand in the local marketplace. Early detection through smart techniques may help farmers and the relevant agricultural pathology authority take preemptive measures. The tomato crop will naturally increase in productivity with the early detection of late blight disease through the proposed hybrid strategy. This study used HOG and SVM as hybrid strategies to detect or identify affected leaves in the early stages. HOG extracts features from tomato leaf images, and SVM determines whether a tomato leaf is healthy or infected with the late blight disease.

C. Research Significance

This study highlights the importance of smart agriculture and the need for early detection of tomato diseases, specifically the late blight disease caused by the pathogen Phytophthorainfestans, which results in severe crop losses. The annual production of tomatoes is over 100 million metric tons worldwide, and with the increasing global population and demand for higher crop yields, there is a growing need for smart farming techniques. The development of dark, sunken, and greasy spots on infected fruit is a common symptom of late blight in tomatoes, as shown in figure 2.



Figure 2: Late Blight Tomatoes

This study presented a hybrid approach composed of support vector machines (SVM) and histogram-oriented gradients (HOG) with the aim of detecting the late blight disease in tomato plants in real time. The research objectives are to improve the dataset by including early-affected late blight tomato leaves and to achieve early detection of the disease using the proposed hybrid strategy. Early detection of the disease through this hybrid algorithm could help farmers and relevant authorities take preemptive measures to protect the tomato crop, which could result in an increase in productivity and protect the country's economy.

II. PAPER ORGANIZATION

This paper is structured into seven sections, beginning with an introductory section that discusses the research topic of late blight disease detection and classification in tomato plants using machine learning techniques. It covers the research background and the significance of the study.

The third and fourth sections provide an extensive literature review on late blight disease in tomato plants, covering its management techniques, machine learning algorithms, feature extraction methods, and classification algorithms such as HOG, SVM, Decision Tree, and KNN. These sections also include a comparison of related work.

Section five outlines the research methodology, including data preprocessing, the research flow chart, the simulation environment, dataset details, data splitting, and the proposed HOG-based SVM algorithm.

Section six presents the results and discussions of the research study, including an introduction, preliminary study, performance evaluation, and a summary of the findings. The results demonstrate that the proposed HOG-based SVM algorithm outperforms other classification algorithms, achieving an accuracy rate of 82%.

The final section offers a conclusion to the research study, discussing the research objectives, findings, and contributions in the field of machine learning in plant disease detection and classification. It also discusses future directions, highlighting the importance of improving algorithm accuracy and expanding the research scope to encompass other plant diseases.

III. LITERATURE REVIEW

Arakeri et al. (2015) introduced a technique for detection of tomato leaf diseases based on image processing. They worked on a special disease caused by fungi called late blight. The early signs of this disease are non-uniform leaf shape, water soaked lesions. Their purposed model was to detect and analysis of that disease based on novel computer vision using thresholding algorithm and KMeans clustering algorithm to identify whether a leaf is effected or healthy and achieved accuracy from 80% to 85%.

Durmuş et al. (2017) worked on the detection of tomato leaf diseases in their tomato farm green house. The team investigated those different diseases of the tomato leaves can also be detected by taking a close photograph of the subject using sensors. The main issue with them was the selection of deep learning architecture. So two approaches AlexNet and SqueezeNet were tested, trained and validated on NVidia Jetson TX1. They used healthy plant village tomato leaf dataset and tested their trained network on random online images.

Zhang et al. (2018) used reinforcement learning to identify a disease affecting tomato leaves. They used deep convolution neural network (CNN) that successfully detect tomato leaf disease. The foundation of CNN at that time was made up by AlexNet, GoogleNet, and ResNet. ResNet was the best model with stochastic gradient descent that has the precision of 97.28% for finding tomato leaf disease.

Elhassouny and Smarandache (2019) developed a smart phone application for tomato leaf disease detection. The application was based on deep learning using convolution neural network inspired by MobileNet which is faster and have small architecture. The dataset contains more than 7100 tomato leaves.

Hasan et al. (2019) used transfer learning to detect the tomato leaf disease. They worked on deep learning precision farming using CNN. Most of his work was based on convolution neural network. In order to identify precisely high effective areas, he introduced a drone based farming system. Their dataset consist of 500 images of the effected leaves from a farm and 2100 images from the internet. They used transfer learning to train CNN with 99% accuracy by increasing the training dataset to 85%.

Kumar and Vani (2019) proposed CNN model for the detection of tomato leaf diseases by performing experiments with conventional neural network. To train the deep CCN network plants village dataset was used with 4900 images of dataset including healthy and effected leaves with accuracy of 99%.

Bir et al. (2020) introduced a mobile application to detect the tomato leaf diseases based on transfer learning. Convolution neural network was used for classification and detection of healthy and effected leaves. This method is now recently and widely used methods with the goal to classify and detect the leaves based on smartphones and have found many applications in the field of robotics, healthcare and agriculture.

Zaki et al. (2020) classified tomato leaves diseases based on MobileNetv2 that has more than 50 layers. The small size allows the network to perform much faster. The model was able to detect three types of tomato leaf diseases trained on more than 4500 images of leaves from Plant Village dataset. The algorithm was tested with the same dataset and achieved accuracy of 92%.

Ashok et al. (2020)diagnosis tomato leaves diseases using deep learning methodology with intensive field work. Most of their work was based on image processing techniques using image segmentation, clustering and open source algorithms. This work helped in identifying different tomato leaves diseases caused by fungi and virus. The disease diagnosis method was very reliable and accurate especially with tomato leaves diseases.

Gadade and Kirange (2021)detected tomato leaf diseases at different phases of development using machine learning. The effectiveness of several classification approaches, such as SVM, KNN, and Nave Bayes, Decision Tree, and LDA was evaluated. The study showed that the model offers useful method for classifying the level of tomato leaf spot. They used machine learning approach while the accuracy is not mentioned.

Sharmila et al. (2021) carried out their work on the classification of pest that causes diseases in tomato leaves. The classification was based on seven models where the proposed CNN model showed an average accuracy of 93% and more accurate than other conventional machine learning models.

Nanni et al. (2022) tried different learning model such as ResNet, MobileNet and GoogleNet with different dataset. The data they used was Deng small and IP102 dataset mostly used for pest recognition. They modified their model with Adam optimizer with 96% accuracy for small dataset and 78% accuracy for IP102 dataset.

IV. RELATED WORK

Several techniques have been proposed for identifying and categorizing tomato leaf diseases using machine learning algorithms. Arakeri et al. (2015) used image processing to detect late blight disease with 80-85% accuracy. Durmuş et al. (2017) employed deep learning methods, specifically the AlexNet and SqueezeNet architectures, on the Healthy Plant Village dataset and achieved high precision. Zhang et al. (2018) utilized a deep CNN model with reinforcement learning to attain 97.28% accuracy in detecting tomato leaf disease.

Similarly, Hasan et al. (2019) achieved 99% accuracy on their dataset using transfer learning and CNN. Kumar and Vani (2019) reported similar accuracy rates of 99% using the Healthy Plant Village dataset with a CNN model. Bir et al. (2020) created a mobile application for tomato leaf disease detection by employing transfer learning and CNN. Smarandache (2019) developed a Elhassouny and smartphone application using MobileNet-based architecture that performed with high accuracy on a dataset containing more than 7100 tomato leaves. Nanni et al. (2022) compared the accuracy of various CNN models on different datasets, achieving 96% and 78% for small and IP102 datasets, respectively. Sharmila et al. (2021) employed a CNN model for the classification of pests that cause diseases in tomato leaves with an average accuracy of 93%. Zaki et al. (2020) reported 92% accuracy using MobileNetv2 for tomato leaf disease classification. Gadade and Kirange (2021) evaluated the efficacy of several classification methods such as SVM, KNN, and Naive Bayes, Decision Tree, and LDA at different stages of tomato leaf disease development, while Ashok et al. (2020) applied deep learning techniques to identify various tomato leaf diseases caused by fungi and viruses reliably and accurately.

The utilization of machine learning algorithms, such as SVM with HOG, can be a cost-effective alternative to neural networks for tomato leaf disease classification.

V. RESEARCHMETHODOLOGY

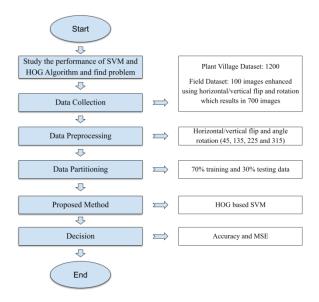


Figure 3: Proposed Methodology

A. Study and Problem

The research methodology employed in this study, which primarily revolves around evaluating the efficacy of the HOG-based SVM algorithm for detecting late blight tomato disease. The main objective of the research is to address the issue of early detection and management of the disease, with the aim of improving tomato production outcomes.

B. Data Collection

In the second phase of the research, the focus is on assembling the dataset for late blight tomato disease. This is

achieved by gathering a collection of 1200 images from the Plant Village dataset obtained from Kaggle as shown in figure 4, along with an additional 100 images captured directly from the tomato field as shown in figure 5. To enrich the custom dataset, data augmentation techniques, including horizontal/vertical flipping and rotation, are applied to the 100 field images. Consequently, the dataset expands, resulting in a total of 700 images. This comprehensive dataset serves as a foundation for subsequent analysis and experimentation in the study.



Figure 4: Dataset from Kaggle



Figure 5:Dataset from Field



Figure 6: Field of Dataset Collection

Link to the Field Map:

https://goo.gl/maps/UggWPAetbU83M8LK6



Figure 7: QR-Code to Map of Tomato Field

C. Data Preprocessing

In the research methodology, the third stage involves data preprocessing aimed at augmenting the custom dataset. This is accomplished by applying transformations such as horizontal/vertical flip and rotation at specific angles (45, 135, 225, and 315 degrees). These preprocessing techniques are implemented to enhance the dataset's diversity and facilitate improved performance in subsequent stages of the study.

D. Data Partitioning

The dataset is partitioned into two subsets: training and testing. The training subset comprises 70% of the total dataset, while the remaining 30% is allocated for testing purposes. It is important to note that the dataset consists of a total of 1900 images. This partitioning strategy ensures a suitable distribution of data for training the model and evaluating its performance accurately during testing.

Table 1: Data Partition

Dataset	No. of Images
Training	1330
Testing	570
Total	1900

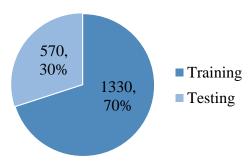


Figure 8: Data Distribution

E. HOG based SVM

The proposed HOG-based SVM algorithm is utilized to enable early detection of late blight tomato disease. Implemented in Jupyter Notebook and Python, the algorithm undergoes training using a labeled dataset comprising 1330 images. The HOG technique acts as a feature descriptor, partitioning the image into smaller cells and calculating gradient orientation and magnitude within each cell. This extraction process captures pertinent image information. The resulting histograms of gradient orientations are combined to form a feature vector representing the image. Subsequently, the SVM classifier is trained using these feature vectors to classify new images as infected or healthy.

To facilitate training the SVM classifier for late blight tomato disease classification, a labeled dataset containing images of both infected and healthy tomato plants is employed. The HOG feature descriptor is applied to extract distinctive features from these labeled images, enabling the subsequent training of the SVM classifier as shown in figure 9.

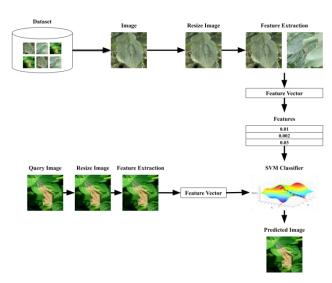


Figure 9: Flow diagram

To enhance the model's performance, the hyperparameters of the SVM classifier, including the regularization parameter and the choice of kernel function, can be adjusted. Additionally, incorporating image processing techniques like image segmentation can further improve system accuracy. These additional techniques complement the HOG-based SVM approach, refining the classification process.

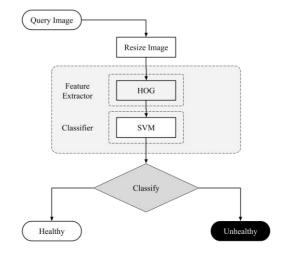


Figure 10: Graphical sketch of the proposed model

The graphical representation of the proposed HOG-based SVM model for the classification of late blight tomato leaf disease is shown in figure 10. The proposed model's pseudo code is provided for more detailed overview;

Pseudo code: HOG based SVM for Classification of Late Blight Tomato Leaf Disease

- 1. Start
- 2. Input: Late blight tomato leaf dataset
- 3. Output: Detection of late blight tomato disease
- 4. Input: Image of tomato leaf
- Initialize: HOG descriptor for feature extraction and SVC for detection

- **6. HOG:** Extract features from the images and convert into vector format
- 7. SVM: Detect late blight disease in tomato leaf image
- **8.** Evaluate: MSE, accuracy, precision, and recall
- 9. Output: Prediction of late blight disease for tomatoleaf

10. End

The given pseudo code provides an overview of the steps involved in applying HOG-based SVM to classify late blight tomato leaf disease. The process begins by initializing the HOG descriptor and SVM classifier using a dataset of late blight tomato leaf images. Then, a tomato leaf image is processed using the HOG technique to extract its features, which are transformed into a vector format. The SVM classifier is employed to determine whether the image exhibits late blight disease. Performance evaluation is conducted using metrics such as MSE, accuracy, precision, and recall. Finally, the model predicts the presence or absence of the late blight disease in the examined tomato leaf.

F. Evaluation Parameters

Performance evaluation parameters, including the confusion matrix, accuracy, precision, recall, and Mean Square Error (MSE), are essential for assessing model effectiveness and guiding improvements.

1) Accuracy

Accuracy refers to the ability of an instrument to measure a value with precision, indicating how closely the measured value aligns with the reference or actual value. To enhance accuracy, smaller readings can be taken, which helps to minimize the level of inaccuracy in the calculation. By incorporating smaller readings, the precision of the measurement is improved, thereby reducing the margin of error in the calculation.

Accuracy=
$$\frac{(TP+TN)}{(Tp+TN+FP+FN)}$$
 (Eq. 1)

2) Precision

Precision is a metric used to assess the accuracy of positive predictions by evaluating the ratio of true positive instances to the total number of instances that were predicted as positive. It quantifies the proportion of correctly identified positive cases among all the instances classified as positive.

Precision =
$$\frac{TP}{(TP+FP)}$$
 (Eq. 2)

3) Recall

Recall measures the proportion of true positive instances correctly predicted among all the actual positive instances present in the dataset. It quantifies the ability of a model to capture and identify positive cases accurately.

Recall =
$$\frac{TP}{(TP+FN)}$$
 (Eq. 3)

4) Mean Squared Error (MSE)

The Mean Squared Error (MSE) of estimators is computed as the square root of the average error between the predicted and expected values. It offers a convenient method for calculating the gradient. By considering both large and small values, we can emphasize how closely the fitted line aligns with the data. For the specific formula used in calculating the mean square error, please refer to the provided link.

Mean Square Error (MSE) =
$$\frac{1}{n}\sum_{i=1}^{n}(xi - yi)^2$$
(Eq. 4)

5) Confusion Matrix

The confusion matrix provides valuable insights into classifier's accuracy and misclassifications (Maheswaran et al., 2022; Ting et al., 2010). It is a twodimensional matrix that represents the classification performance of a classifier, indexed by the true class of an object and the class assigned by the classifier. For this study,the matrix is divided into four cells: true positive, false negative, false positive and true negative. True positive indicates the number of positive samples correctly identified as positive by the model. False negative represents the instances where a positive sample was incorrectly classified as negative. False positive represents the cases where a negative sample was wrongly classified as positive. True negative indicates the number of negative samples correctly identified as negative by the model.

		Assigned Class	
		Positive	Negative
Vegative Negative	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

Figure 11: Confusion Matrix

VI. EXPERIMENTAL RESULTS

A. Accuracy and MSE

The research examined the accuracy and MSE values for three models: the proposed HOG based SVM, HOG with Decision Tree (DT), and HOG with K-nearest neighbors (KNN). The HOG + SVM model achieves the highest accuracy of 0.82 and the lowest MSE of 0.177193, indicating its superior performance in detecting late blight tomato disease. In comparison, the HOG + DT model has a higher MSE of 0.340351 and a lower accuracy of 0.66. The HOG + KNN model performs even worse, with an accuracy of 0.442105 and an MSE of 0.56. The numbers clearly shows that HOG based SVM model outperforms the other models in terms of accuracy and MSE as shown in table 2.

Table 2: Accuracy and MSE of HOG based SVM

Model	Accuracy	MSE
HOG + SVM	0.82	0.177193
HOG + DT	0.340351	0.66

HOG + KNN 0.442105	0.56
--------------------	------

B. Classification Report

The research presents the classification report of the HOG based SVM model, including precision, recall, and F1-score values for two classes. Class 0 has a precision of 0.804636, recall of 0.852632, and F1-score of 0.827939, while class 1 has a precision of 0.843284, recall of 0.792982, and F1-score of 0.81736. The model achieves an overall accuracy of 0.82396, with macro-averaged precision, recall, and F1-score of 0.804636, 0.852632, and 0.827939, respectively as shown in table 3.

Table 3: Classification Report of HOG based SVM

	Precision	Recall	F1-Score
0	0.804636	0.852632	0.827939
1	0.843284	0.792982	0.81736
accuracy	0.82396	0.822807	0.822649
macro avg	0.804636	0.852632	0.827939
weighted avg		0.652052	0.021939

The classification report of the HOG-based DT model, with class 0 precision, recall, and F1-score of 0.64918, 0.694737, and 0.671186, and class 1 precision, recall, and F1-score of 0.671698, 0.624561, and 0.647273. The model's accuracy is 0.660439, and its macro-averaged precision, recall, and F1-score are 0.64918, 0.694737, and 0.671186, respectively as shown in table 4.

Table 4: Classification Report of HOG based DT

	Precision	Recall	F1-Score
0	0.64918	0.694737	0.671186
1	0.671698	0.624561	0.647273
accuracy	0.660439	0.659649	0.65923
macro avg	0.64918	0.694737	0.671186
weighted avg	0.04918	0.094737	0.071180

Table 5 provides the classification report of the HOG-based KNN model, indicating class 0 precision, recall, and F1-score of 0.537079, 0.838596, and 0.654795, and class 1 precision, recall, and F1-score of 0.632, 0.277193, and 0.385366. The model achieves an accuracy of 0.584539, and its macro-averaged precision, recall, and F1-score are 0.537079, 0.838596, and 0.654795, respectively.

Table 5: Classification Report of HOG based KNN

	Precision	Recall	F1-Score
0	0.537079	0.838596	0.654795
1	0.632	0.277193	0.385366
accuracy	0.584539	0.557895	0.52008
macro avg	0.537079	0.838596	0.654795
weighted avg			

C. Confusion Matrix

The figure 12 reveals that the HOG with SVM model for late blight tomato accurately predicted 243 instances of healthy tomatoes as true negatives (TN) and 226 instances of late blight tomatoes as true positives (TP). However, there were 42 instances of healthy tomatoes that were falsely predicted as late blight (false positives, FP) and 59 instances of late blight tomatoes that were falsely predicted as healthy (false negatives, FN).

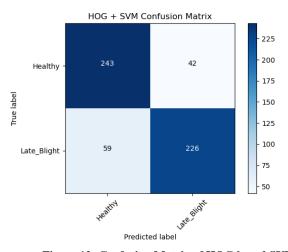


Figure 12: Confusion Matrix of HOG based SVM

The figure 13 represents the confusion matrix of the HOG with Decision Tree model for late blight tomato shows that the model accurately classified 198 instances of healthy tomatoes as true negatives and 178 instances of late blight tomatoes as true positives. However, there were 87 false positive predictions, indicating that 87 instances of healthy tomatoes were incorrectly classified as late blight. Additionally, the model had 107 false negative predictions, meaning that 107 instances of late blight tomatoes were wrongly classified as healthy.

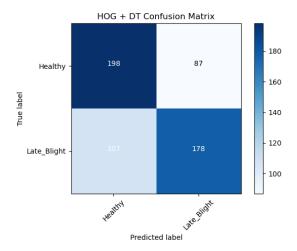


Figure 13: Confusion Matrix of HOG based DT

The confusion matrix of HOG based KNN for late blight tomato reveals that the model accurately classified 239 instances of healthy tomatoes and 79 instances of late blight tomatoes. However, there were 46 false positive predictions, indicating that 46 instances of healthy tomatoes were incorrectly classified as late blight. In addition, there were 206 false negative predictions, meaning that 206 instances of late blight tomatoes were wrongly classified as healthy. The model exhibited a higher number of false positives for late blight tomatoes and a higher number of false negatives for healthy tomatoes.

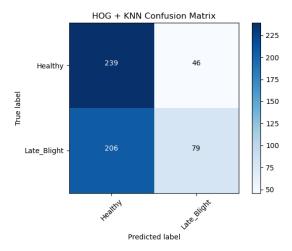


Figure 14: Confusion Matrix of HOG based KNN

VII. CONCLUSION

The research study compared the effectiveness of Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM), Decision Tree, and K-Nearest Neighbors (KNN) models in predicting late blight disease in tomatoes. The experimental results demonstrated that the HOG with SVM model outperformed the other models, achieving a lower Mean Squared Error (MSE) of 0.1772 and a higher accuracy of 0.82. The classification report revealed that the HOG with SVM model exhibited high precision, recall, and f1-score values for both healthy and late blight tomatoes disease, indicating its effectiveness in predicting the disease. The macro average precision, recall, and f1-score values were also high at 0.82, demonstrating the model's

performance across all classes. The confusion matrix further supported the findings, showing accurate identification of true positives and true negatives by the HOG with SVM model.

The proposed HOG based SVM model can be utilized to create efficient and automated detection systems, which can greatly reduce crop losses and enhance agricultural productivity. The enriched image dataset resulting from this research can contribute to future studies aiming to improve the accuracy of machine learning models in detecting the disease. It makes valuable contributions to the advancement of effective methods for detecting and preventing late blight tomato leaf disease, thereby benefiting the agricultural industry.

REFERENCES

- Ashok, S., Kishore, G., Rajesh, V., Suchitra, S., Sophia, S. G., & Pavithra, B. (2020). Tomato leaf disease detection using deep learning techniques. 2020 5th International Conference on Communication and Electronics Systems (ICCES).
- [2] Arakeri, M. P., Arun, M., & Padmini, R. (2015). Analysis of late blight disease in tomato leaf using image processing techniques. International Journal of Engineering and Manufacturing (IJEM), 5(4), 12-22
- [3] Bir, P., Kumar, R., & Singh, G. (2020). Transfer learning based tomato leaf disease detection for mobile applications. 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON).
- [4] Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05).
- [5] Durmuş, H., Güneş, E. O., & Kırcı, M. (2017). Disease detection on the leaves of the tomato plants by using deep learning. 2017 6th international conference on agro-geoinformatics,
- [6] Elhassouny, A., & Smarandache, F. (2019). Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks. 2019 International Conference of Computer Science and Renewable Energies (ICCSRE).
- [7] Gadade, H., & Kirange, D. (2021). Machine Learning Based Identification of Tomato Leaf Diseases at Various Stages of Development. 2021 5th International Conference on Computing Methodologies and Communication (ICCMC).
- [8] Hasan, M., Tanawala, B., & Patel, K. J. (2019). Deep learning precision farming: Tomato leaf disease detection by transfer learning. Proceedings of 2nd international conference on advanced computing and software engineering (ICACSE).
- [9] Kumar, A., & Vani, M. (2019). Image based tomato leaf disease detection. 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT).
- [10] Maheswaran, S., Sathesh, S., Kumar, A., Hariharan, R., Ridhish, R., & Gomathi, R. (2022). YOLO based Efficient Vigorous Scene Detection And Blurring for Harmful Content Management to Avoid Children's Destruction. 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC).
- [11] Nanni, L., Manfè, A., Maguolo, G., Lumini, A., & Brahnam, S. (2022). High performing ensemble of convolutional neural networks for insect pest image detection. Ecological Informatics, 67, 101515.
- [12] Sharmila, V. C., Chauhan, N., Kumar, R., & Barwal, S. (2021). Design of Intelligent Insect Monitoring System Using Deep Learning Techniques. Proceedings of the First International Conference on Computing, Communication and Control System, I3CAC 2021, 7-8 June 2021, Bharath University, Chennai, India.
- [13] Ting, J.-A., Vijayakumar, S., & Schaal, S. (2010). Encyclopedia of machine learning. In Encyclopedia of Machine Learning (pp. 613-624). springer us.
- [14] Tyagi, M. (2021). HOG(Histogram of Oriented Gradients). Towards Data Science. https://towardsdatascience.com/hog-histogram-of-oriented-gradients-67ecd887675f.

- [15] Zaki, S. Z. M., Zulkifley, M. A., Stofa, M. M., Kamari, N. A. M., & Mohamed, N. A. (2020). Classification of tomato leaf diseases using MobileNet v2. *IAES International Journal of Artificial Intelligence*, 9(2), 290.
- [16] Zhang, K., Wu, Q., Liu, A., & Meng, X. (2018). Can deep learning identify tomato leaf disease? Advances in multimedia, 2018.