# Bell Pepper Leaf Disease Classification Using Support Vector Machine

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**Abstract.** Bell Pepper is a plant commonly cultivated in India and a significant exporter to various foreign nations. Bell Pepper is a type of plant that is mainly utilized as a spice. However, bacterial infection occurs while crop cultivation is rapidly increasing, leading to low-quality exports and degraded levels of spice content in the plants. In our paper, we utilize the classification technique of Support Vector Machine (SVM) to extract the features of the plant leaves and develop an algorithm to accurately classify the bacterial leaves to prevent the further spread of the disease. The overall process encompasses utilizing an image dataset containing images of diseased and healthy plants, converting the images into a gray scale version, extracting the image's essential features, and utilizing the image to receive an accurate result from the classifier. This research will identify the rotten plants by detecting the bacterial spots present in the leaves and save the time and effort of the farmers cultivating the plants.

**Keywords:** Bell Pepper, Support Vector Machine, Classify, image dataset, bacterial leaves

## 1 Introduction

Bell Pepper, commonly known as capsicum, is a vegetable plant that originated in America. However, depending upon the place of cultivation, it can be further segregated into different types such as chili pepper, green pepper, paprika, etc. The capsicum, distributed across the globe, is initially cultivated in a greenhouse plantation using cultivators that continuously produce the vegetable under favorable climatic conditions and utilize fertilizers to ensure the plant's safety from pesticides. India is globally ranked fourth in the production and distribution of bell pepper, and it is more prevalent in the states of Tamil Nadu, Karnataka, Andhra Pradesh, Uttar Pradesh, and Maharashtra. The export of bell pepper is highly demanding, and their quality depends upon factors such as size, color, and shelf life; however, producing high-quality pepper is affected by external environmental factors such as pests, infection, and leaf diseases.

The main objective of the implementation paper is to identify and classify the different types of leaf diseases that occur in bell pepper plants using image processing and machine learning. Leaf

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diseases are common problems for various types of plants and crops. The diseases can be classified into pathogens, leaf spots, rust, bacterial blight, and viruses. The diseases can significantly impact vegetable growth, yield, and quality. The harmful side effects of these diseases are a reduction in photosynthesis, nutrient uptake, and water intake, increased susceptibility to other diseases, soil erosion, decreased export quality, and market value. Image processing and machine learning are two fields that are widely applied in various real-world situations. Image processing is always used in the preprocessing stage of a machine learning algorithm to extract crucial features from images, such as edges, textures, shapes, and colors. That features will act as a significant component in the training phase of a machine learning model to recognize those features and identify the objects present in the images uploaded in the testing phase. Machine Learning, on the other hand, is used to automate specific tasks, such as image classification, segmentation, and restoration in image processing. The concept of machine learning comes in handy during instances such as learning hidden patterns among images from a large dataset. An example is the detection of tumors in medical images or enhanced images having a lower resolution. Using techniques available in computer vision enables many field applications in agriculture, and its main advantages over existing techniques are improved accuracy and speed, automation, and various possibilities for innovations.

Image enhancement techniques are performed in the leaf images before starting the next step as it provides more detail and eliminates unwanted pixels. That process saves time for the upcoming set of an algorithm to identify and classify the images. The HOG (Histogram of Oriented Gradients) algorithm is utilized for detecting and recognizing the features present in the images; it calculates the distribution of gradient orientations in an image and represents it as a feature vector random. However, this process requires three main components. First and foremost, the first component required for HOG feature extraction is Hu moments. They are a statistical measure that quantifies the distribution of pixel intensities in an image. Hu moments are defined into seven moments, each of which describes a critical aspect of the image, such as the spread of the object in every direction, skewness, rotation, thickness, and roundness of an image. It is better to perform this step after the conversion of the image from RGB to Grayscale so that it provides an array of shape descriptors. The next component is Haralick Texture which uses GLCM (Grey Level Co-occurrence Matrix) to describe the frequency of pixels value at different spatial offsets within an image. Haralick Texture includes features such as homogeneity, entropy, and correlation from a given image and is commonly used to analyze an image's Texture. The final component is the Color histogram, which displays the number of pixels in the image containing similar colors and is first converted into HSV (Hue Saturation Value) to represent different color spaces. The primary purpose of color histograms in image processing is to identify the region of interest or distinguish between different objects based on their colors.

Random Forest is applied as the classifier to create multiple decision trees to classify input images using their features independently, and it receives the feature of an image by HOG, Haralick Texture, and Color histogram; The Random Forest classifier will classify and label the leaf images using the features extracted and provide results according to the type of the plant, and it is disease variation. The classifier must be provided with lots of training images as a sample to identify the pattern in the image and give a test set of images to validate the accuracy of the classifier. If the accuracy of the classifiers is satisfactory, they can be used on larger image datasets to perform similar actions. The advantage of using random forest is its ability to deal with noisy, missing data and handle large datasets with high dimensionality..

## 2 Review of Literature

Sharada Mohanty[1] implemented a deep-learning algorithm for image-based plant disease detection. The dataset for analysing the plant disease included 54,306 images of plant leaves, classified into 38 pairs of leaves and their related diseases. The dataset was divided into three parts, where the test was performed on coloured images of leaves. Then, a grey-scaled version of the same and finally, the image of leaves segmented and without any background in order to reduce the chance of bias, The methodology involved Alex Net and Google Net deep Learning architecture with two training mechanisms – Transfer Learning and Training from Scratch and the deep learning model is trained and tested at various ratios such as (80-20, 60-40, 50-50, ETC…). The model's performance is analysed using various metrics such as F1-Score, Precision, Recall, and Mean to measure the average performance and accuracy of the model. The results concluded that transfer learning is best suited to train deep learning models and an 80-20 train test ratio and dataset with coloured leaves image fetches the highest accuracy of 99.35%. The suggested model's challenge is that it lacks accuracy when new test images are given to the classification model, as it lacks diverse images of leaves. Also, the classifier could accurately predict the category of leaves only when the images were captured under a homogeneous background.

Shima Ramesh [2] proposed random forest classification in machine learning to categorize the leaves as healthy and diseased based on the extracted features of the images fed into the model. Pre-processing of the image brings all the images size to a reduced uniform size. Haralick Texture is used to distinguish between healthy and diseased leaves, the labelled image is segregated into training, and the testing dataset is given to HOG (Histogram of Oriented Gradients) to extract the necessary features. The Random Forest model is used to classify leaves based on the extracted features, the RGB image is first converted to HSV color space, and the histogram is calculated for the same. It is needed to convert the RGB image to HSV since the HSV model aligns closely with how the human eye discerns the colors in an image. First, we need to convert the RGB image into a grayscale image for any image. This is done because Hu moments shape descriptor and Haralick features can only be calculated over a single channel. Therefore, it is necessary to convert RGB to grayscale before computing Hu moments and the Haralick feature. To calculate the histogram, the image first must be converted to HSV (hue, saturation, and value), so we are converting the RGB image to an HSV image. The result is displayed as a healthy or diseased leaf. The accuracy of the random forest model is compared with other machine Learning models. The model with the highest classification is Random Forests 70.14, K- nearest neighbor 66.76, regression 65.33, Support vector machine 40.33, CART 64.66, and Naïve Bayes 57.61. The model is given 160 images of papaya leaves as input, and the model could classify with approximately 70 percent accuracy. The accuracy can be increased when trained with a vast number of images and by using other local features together with the global features such as SIFT (Scale Invariant Feature Transform), SURF (Speed Up Robust Features), and DENSE along with BOVW (Bag Of Visual Word).

S.Ashwinkumar [3] proposed an OMNCNN model that operates on different stages: pre-processing, segmentation, feature extraction, and classification. Manjunatha Badiger [4] proposed an Image processing technique that can be used for disease detection, involving mathematical equations and transformations. From an image, human eyes will only pursue the colors, but extracting features from the image is possible. The work is carried out through K-means clustering and support vector machine using MATLAB software through which leaf and skin diseases are classified. The threshold value is set between 0-256 using the OTSU threshold algorithm to specify the affected areas in images. Also, GLCM (grey-level Co-occurrence matrices are used to extract the textural aspects of the input image. The accuracy level for classification while using K-means and SVM results to 96% compared to other techniques such as PNN, RBG imaging, etc.

Konstantinos P. Ferentinos [5] mentions a Convolution Neural Network utilized for layer-by-layer classification for image recognition, and the five main CNN architectures are AlexNet, AlexNet OWTBN, Google Net, Over feat, and VGG(Visual Geometry Group). The dataset utilized for training the model included 87,848 images containing 25 varieties of plants. The test-train ratio is 80-20, and Torch-7 Machine Learning computational framework is utilized. VGG fetched the highest classification accuracy with 99.53%, including 17,584 unseen test images.

Sunil S. Harakannanavar's [6] proposed model uses computer vision techniques, including RGB conversion to grey, HE, K-means clustering, and contour tracing is employed in the preprocessing stage. Radhika Bhagwat [7] proposes A comprehensive multilayer convolution neural network(CMCNN) is proposed in this paper for plant disease detection. The classification accuracy for dataset1, dataset2, and dataset3 achieved is 99.85%, 97.16%, and 99.6%, respectively. Mohit Agarwal[8] suggests a lightweight Convolution Neural Network model classify nine types of diseases in tomato crops. For experimental purposes, data has been taken from the PlantVillage dataset. June Chena [9] suggests a transfer learning for deep CNNs is studied to enhance the learning ability of tiny lesion symptoms, and a novel deep learning architecture called INC- VGGN is proposed for the identification of plant disease images.

## 3 Methodology

### 3.1 Input Image

In image processing, an input image refers to a digital image being analyzed or processed by a computer program or algorithm [10,11]. The image is initially provided as input to the processing system and on which various operations are performed, such as filtering, enhancement, segmentation, feature extraction, and object recognition. An input image can be obtained from various sources, such as digital cameras, scanners, medical imaging devices, satellite sensors, etc. The quality and characteristics of the input image can significantly affect the accuracy and efficiency of the image processing algorithms, so it is crucial to preprocess or normalize the image, if necessary, to ensure that it meets the requirements of the application or task [12, 13]. The dataset utilized for this research involves the bell pepper images from the Plant Village Dataset, which consists of 2745 images of 256 by 256 pixels of bell pepper plants and is subdivided into Bacterial Spot and Healthy images.

### 3.2 Pre-Processing

The initial step before the classification of an image lies with preprocessing mainly because a raw image will contain 'noise' or redundant features present, which will cause hindrance to the overall performance of the classifier. Preprocessing also reduces computational complexity since grayscale images have only one-color channel, meaning they are simpler and faster to process than color images, which typically have three color channels (red, green, and blue). Grayscale images require less storage and processing power, which can be crucial in applications where speed and efficiency are critical [14, 15]. It also reduces noise, as grayscale images are often less noisy than color images because noise tends to be more visible in the color channels than in the luminance channel, and by converting to grayscale, the impact of the noise is reduced. In some applications, it may be helpful to standardize the color space of the images being processed. Grayscale images provide a standard color space that is independent of the original color space of the input image. Overall, grayscale conversion can be an excellent preprocessing step in image processing, as it simplifies the image and can help to highlight important features.

The next step in Preprocessing involves splitting the dataset into training and testing components [16, 17]. The dataset is split in the ratio of 70:30. The 70% of data is considered as training dataset and 30% is considered as testing dataset.

### 3.3 Feature Extraction

The most commonly used feature extraction technique in image processing and computer vision and machine vision is bag of features [18, 19]. In this technique, the visual features are extracted using SIFT and HoG techniques. The bag of features function extracted 101986 features from 742 images from the training dataset. SURF (Speeded-Up Robust Features) is a popular algorithm for feature detection and matching in image processing. It detects distinctive features, or critical points, in an image and then describes each key point using a set of descriptors. In the leaf dataset, all the relevant will be extracted and used to match critical points across different images, which helps recognize the infected region in the testing dataset.

### 3.4 Classification

Support vector machines (SVMs) are widely used in image processing for various tasks, such as classification, segmentation, and object detection [20]. SVMs are supervised learning models that classify data into different classes based on labeled examples. The basic idea behind SVMs is to find the hyperplane that separates the data points of different classes with the maximum margin. The features extracted from the leaf images are utilized in the classifier to predict healthy leaves from bacterial spot leaves accurately. In a binary classification problem, the hyperplane is a linear decision boundary that separates the two classes. SVMs find the hyperplane that maximizes the margin between the closest data points from each class, known as the support vectors. This approach ensures that the model is robust to noise and can generalize well to new data points.

In the case of non-linearly separable data, SVMs can use kernel functions to transform the data into a higher- dimensional feature space where the classes are separable by a hyperplane. The kernel function maps the original data into a higher-dimensional space without computing the coordinates of the data in that space. This approach allows SVMs to capture complex patterns in the data and improve the classification performance. SVMs can handle both linear and non-linear classification tasks and can be used for binary classification as well as multi- class classification. SVMs have several advantages over other classification algorithms such as logistic regression, decision trees, and random forests.

## 4 Conclusion

A Confusion Matrix is utilized to evaluate the performance of the classifier. A confusion matrix is a table used to evaluate a machine-learning model's performance. It is a square matrix that compares a model's predicted labels to the accurate data labels. A confusion matrix is a helpful tool for understanding the accuracy and precision of a model and can be used to in- tune the model for better performance. SVM (Support Vector Machine) can accurately predict the infected bacterial leaf from the healthy leaf with 80 percent accuracy. The overall performance of the SVM classifier is accurate enough to predict the pepper bell images and distinguish it between bacterial spot and healthy.

## References

[1] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in plant science, 7, 1419.

[2] Ramesh, S., Hebbar, R., Niveditha, M., Pooja, R., Shashank, N., & Vinod, P. V. (2018, April). Plant disease detection using machine learning. In the 2018 International conference on design innovations for 3Cs compute communicate control (ICDI3C) (pp. 41-45). IEEE.

[3] Ashwinkumar, S., Rajagopal, S., Manimaran, V., & Jegajothi, B. (2022). Automated plant leaf disease detection and classification using optimal MobileNet-based convolutional neural networks. Materials Today: Proceedings, 51, 480-487.

[4] Badiger, M., Kumara, V., Shetty, S. C., & Poojary, S. (2022). Leaf and skin disease detection using image processing. Global Transitions Proceedings, 3(1), 272-278.

[5] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and electronics in agriculture, 145, 311-318.

[6] Harakannanavar, S. S., Rudagi, J. M., Puranikmath, V. I., Siddiqua, A., & Pramodhini, R. (2022). Plant leaf disease detection using computer vision and machine learning algorithms. Global Transitions Proceedings, 3(1), 305-310.

[7] Bhagwat, R., & Dandawate, Y. (2021). Comprehensive Multilayer Convolutional Neural Network for Plant Disease Detection. International Journal of Advanced Computer Science and Applications, 12(1).

[8] Agarwal, M., Gupta, S. K., & Biswas, K. K. (2020). Development of an Efficient CNN model for Tomato crop disease identification. Sustainable Computing: Informatics and Systems, 28, 100407.

[9] Chen, J., Chen, J., Zhang, D., Sun, Y., & Nanehkaran, Y. A. (2020). Using deep transfer learning for image-based plant disease identification. Computers and Electronics in Agriculture, 173, 105393.

[10] Surya Prabha, D., & Satheesh Kumar, J. (2015). Assessment of banana fruit maturity by image processing technique. Journal of food science and technology, 52, 1316-1327.

[11] Prabha, D. S., & Kumar, J. S. (2014). Study on banana leaf disease identification using image processing methods. Int J Res Comput Sci Inf Technol, 2(2), 2319-5010.

[12]Prabha, D. S., & Kumar, J. S. (2012). A study on image processing methods for fruit classification. In Proc. Int. Conf. on Computational Intelligence and Information Technology, CIIT (pp. 403-406).
[13] D. Surya Prabha, J. Satheesh Kumar, & Gokulakrishnan, R. (2014, July). A Survey on Applications of Image Processing Methods in Agriculture Sector. In International Conference on Convergence Technology (Vol. 4, No. 1, pp. 997-999).
[14] Prabha, D. S., & Kumar, J. S. (2012, October). Crop disease identification using image processing methods. In Proceedings of the National Conference on Green Computing Organized by Department of Computer Science & Research Centre, ST Hindu College, Nagercoil, Tamil Nadu, India (pp. 5-6).
[15] PRABHA, D. S. (2018). Development Of An Efficient Model For Banana Grading And Crop Disease Analysis Using Optimized Image Enhancement And Segmentation Algorithms.
[16] Deenan, S. P., & SatheeshKumar, J. (2014). Image processing methods and their Role in the agricultural sector–A study. International Journal of Business Intell agents., 3, 366-373.
[17] Prabha, D. S., & Kumar, J. S. (2016). Performance evaluation of image segmentation using objective methods. Indian J. Sci. Technol, 9(8), 1- 8.
[18] Prabha, D. S., & Kumar, J. S. (2013). Three-dimensional object detection and classification methods: a study. Int. J. Eng. Res. Sci. Tech, 2(2), 33-42.
[19] Prabha, D. S., & Kumar, J. S. (2016, October). Performance analysis of image smoothing methods for a low level of distortion. In 2016 IEEE International Conference on Advances in Computer Applications (ICACA) (pp. 372-376). IEEE.
[20] Prabha, D. S., & Kumar, J. S. (2013, January). Hybrid segmentation of peel abnormalities in banana fruit. In IJCA Proceedings of the International Conference on Research Trends in Computer Technologies, Coimbatore, Tamil Nadu, India (pp. 30-31)