J. Electrical Systems 20-3 (2024): 1577-1584

[1] Chauhan Pareshbhai Mansangbhai

[2] Chintan Makwana

[3] Hardikkumar Harishbhai Maheta

Chili Disease Detection Using HOG with Euclidean Distance

Journal of Electrical Systems

Abstract: - In order to detect plant diseases in the leaves of chili plants, automatic learning is used in this study. Farmers are planting chilies with the intention of exporting them worldwide. Chili is a need for regular meals. There aren't many illnesses that need to be found in the leaves of chili plants. There are three types of chili plants: weak, diseased, and healthy. Weak and sick chili plants can be affected by diseases such as a harsh leaf, spot leaf, whitefly, yellowish, etc. It has been reported that research is underway to determine whether chile plants are safe to grow or polluted. But when it comes to agriculture, it's critical to recognize the damaged plant by its unique type. Various category diseases are studied using the HOG (Histogram of Oriented Gradients) of the leaf of the chili plant. The representative feature vectors in the feature vector are created using the mean value of every feature point. A typical feature vector and the Euclidean distance are used to calculate the outliers. For the Euclidean distance larger than 0.0025, 0.0016, and 0.00125, the average accuracy rate was 61.6%, 73.2%, and 81.00%, respectively, with the modified border point in the feature vector being 0.0016, 0.00125, and 0.0009. The results presented above suggest that machine-learning techniques for image processing can be used to determine the type of plant disease.

Keywords: Chili Leaf Diseases, Machine Learning, Euclidean distance, HOG, Outlier.

I. INTRODUCTION

The plant diseases are currently detected by straightforward physical eye monitoring, which requires domain knowledge of the disease kind. It requires a great deal of time, money, and specialized knowledge, all of which are needed. In several nations, farmers and individuals lack adequate resources or knowledge about how to consult specialists. Many farmers would like to use new agricultural practices, but they are unable to do so for a variety of reasons, including the expensive cost of the technology and the requirement to learn about the newest innovations [1]. Machine learning-based approaches have gained fame in current days for determining whether or not chili leaves are diseased.

Living (biotic) and non-living (abiotic) agents are the two categories of elements that have the potential to kill and destroy chili plants. To maintain a competitive edge in international trade and strengthen the nation's economy, agricultural operations are involved in the diagnosis of various kinds of destruction [2].

Since their population fluctuates depending on the climatic conditions, it has been noted that plant diseases are frequently challenging to treat. Traditional agricultural methods are still used by farmers in developing nations to grow chili, which takes longer and involves more labor. Indefinite use of pesticides by farmers can affect both human health and the quality of the plants when identifying the affected part of the chili plant [3].

A lot of machine learning techniques use crisp photos of the afflicted chili leaves as input. The datasets are trained following the required pre-processing, image segmentation, and feature extraction [4]. The aforementioned fundamental actions serve as a broad framework for determining whether or not a chili plant is infected. To prevent the plant from contracting that particular disease in the future, it is also necessary to identify the type of infection that is causing the sickness.

A plant leaf may have color distortion or stunted growth, which could harm the pod as a whole [5]. At that point, pests and illnesses have the potential to kill plants or significantly reduce productivity. If the chile is of poor quality, it will also have an immediate negative impact on human health. However, if plant diseases are accurately detected and discovered early on, crop losses can be avoided and particular therapies can be developed to battle specific infections. Gains for the environment and economy are also a result of these need-based therapies [6].

There are a few types of chili disease [7] are there. They are as follows:

1. Damping off.

[1]*Corresponding author: Assistant Professor, Department of Information Technology, Shantilal Shah Engineering College, Bhavnagar, Gujarat, India, Email: pareshchauhan.ssec@gmail.com

[23]Assistant Professor, Department of Information Technology, Shantilal Shah Engineering College, Bhavnagar, Gujarat, India

2. Die-back and Anthracnose (fruit rot).
3. Choanephora blight/ wet rot.
4. Mosaic complex.
5. Powdery mildew.
6. Cercospora leaf spot.
7. Bacterial leaf spot.
8. Alternaria leaf spot.
9. Fusari jam Witt.
10. IPM for Chili.

There aren't many efficient machine-learning techniques available to determine whether or not chili leaves are infected. However, there is currently no effective machine-learning method available to recognize the sort of illness present in chili leaves. There are phases of manual pre-processing in the current methodologies. The level of illness-type recognition in chili leaves is currently not very high [8]. It can be difficult to identify leaf diseases using simple, straightforward, and effective machine learning algorithms [9, 10].

This paper is ordered in the following manner: section II presents related work to this research. Section III shows the proposed work. Section IV shows experiments and results. In section V, the conclusion and future work is discussed.

II. Related Work

This section gives a brief overview of the literature review.

A. Chili Leaf Disease Analysis with SVM Classification Model [11]

The investigation of image processing methods for recognizing and categorizing leaf disease symptoms in chili crops is described in this work. Numerous pathogens released by leaves are responsible for the general symptoms of many illnesses [12]. A major obstacle for farmers when switching from one illness control strategy to another is the heavy reliance on insecticide. Cultivators are also worried about the significant losses and expensive expenses connected to these endeavors. Benefits to farmers and agricultural scientists will be substantial due to the inexpensive, accurate, automated diagnosis and classification of illnesses according to their particular indications. Diseases of the chili leaf are caused by bacteria, fungi, viruses, and other microbes.

This work describes a system that uses support vector machine learning techniques to detect chili leaf disease. Clear pictures of the impacted chili leaves are the input. The dataset was trained following the required preprocessing, image segmentation, and feature extraction. Upon applying SVM to the test dataset, 5-fold cross-validation produced above linear 85% recognition rate, polynomial 87%, and RBF 90% recognition rate.

B. Comparative Analytics on Chili Plant Disease Using Machine Learning Technique [13]

Their work focuses on exploiting machine learning techniques for illness recognition in chili plants. Three algorithms have been used: Multi-Layer-Perceptron (MLP), Recurrent-Neural-Network (RNN), and Convolutional-Neural-Network (CNN), along with their variations. nations that produce chilies: Turkey, China, India, and the United States. India produces over 49% of the world's chilies (according to 2020). The biggest market in India is in Andhra Pradesh (Guntur), where their varieties are particularly well-liked for their color and pungency [14]. According to their research, there are four different types of chili diseases: leaf-spot, yellowish, leaf-curl, and whitefly.

A comparative analysis of deep-learning methods for detecting chili plant illness, including Convolutional-Neural-Network [15], Recurrent-Neural-Network [16], Multi-Layer-Perceptron [17], and their variations. From the Kaggle dataset, 400 photos are selected, categorized into five groups, and then utilized for additional analysis. Three types of CNN, three variants of RNN, and two variants of MLP are used to analyze each image. According to comparative analytics, lower values correspond to a bigger number of hidden layers and a shorter execution time, respectively [18]. According to the research, the fastest strategy is RNN 1 (33901 in milliseconds), which requires 90% for model building and 10% for testing.

The results of this study suggest that the RNN1 method produces the fewest hidden layers. Consequently, RNN1 with an 80:20 ratio had the longest execution time (58789 milliseconds). Finally, the maximum test accuracy is 72.50% for CNN3 (three invisible layers, 70:30 training to testing proportion) and 20% for MLP1 (two invisible layers, 80:20 training to testing proportion). It may be deduced that these methods could be applied to disease control by employing appropriate spraying techniques and using the appropriate amount of pesticides. A scientist who specializes in agriculture can suggest appropriate rules and regulations based on these findings.

C. Disease Identification in Chili Leaves Using Machine Learning Techniques [19]

The Crop diseases lower crop yields or possibly cause crop death. According to I.C.A.R., the state of Goa has experienced a substantial waning in chile production over the past two years as a result of a virus. The majority of plants either rarely blossom or never flower at all [20]. When a plant does, very seldom, manage to blossom, and then the yield is quite low. The suggested approach looks at the signs to determine whether a crop is diseased. Crops are classified as healthy or diseased by the model utilizing a convolutional neural network for feature extraction and supervised image recognition. To create neural-network models, TensorFlow, Keras, and Google machine learning packages are developed. The concept for the illness detection system's usability is used to create an Android application. Features are extracted using a convolution neural network [21].

They label that dataset using a labeling tool. Naming the leaves as diseased or not is known as labeling, which involves enclosing them with bounding boxes. [x-min, y-min] and [x-max, y-max] are the formats in which bounding boxes are kept, representing the left-up and right-down points of a bounding-box, respectively. Various leaves are identified in a solitary image. With the PASCAL VOC format, annotations are stored in an XML file.

D. Symptom-Based Identification of G-4 Chili Leaf Diseases Based on rotation invariant [22]

One more cost-effective and intuitive method of diagnosing various plant leaf diseases is to closely examine the symptoms on the leaves of the plants to get a sense of the infection [23]. This describes a method for identifying unhealthy plant symptoms by applying the idea of feature learning [24]. Disease detection and analysis via physical means is a labor-exhaustive process that is disposed to human mistakes. As a result, a technique for identifying the symptoms only by obtaining an image of a pepper plant leaf could be designed.

The process includes building the symptom vector feature dataset, extracting the region-of-interest, model-building and testing pictures, extracting signs and features from plant images using centroids, and determining the correlation and similarity between various plant symptoms. This will identify several plant diseases. The percentages for accuracy, sensitivity, specificity, and SVM technique are 74%, 76%, and 72%, respectively.

E. Integrated analysis of machine learning and deep learning in chili pest and disease identification [25]

The One of the most important and valuable vegetable crops in the world is chili. However, the existence of pests and illnesses is one of the main reasons limiting the growth of chilies. While there is no treatment for many conditions, the harm they cause can be managed and controlled. Consequently, accurate diagnosis of chili disease will be encouraged by the usage of an automatic recognition structure based on photos [26]. The characteristics that may be extracted from the pictures are essential for developing an identification system with such accuracy.

In this study, features extracted from chile pests and diseases using a classical approach and features mined via a deep-learning-based method are compared. There were two kinds of insect infestations, five different disease types, and one healthy type among the 974 photos of chili leaves that were gathered. To extract important pest and illness features from the pictures of chili leaves, six conventional feature-based techniques and six deep-learning feature-based techniques were applied [27].

For the identification challenge, the collected characteristics were given as input into three machine-learning classifiers: an artificial-neural-network (ANN), a random-forest (RF), and a support-vector-machine (SVM). The outcomes demonstrated that deep learning feature-based techniques outperformed existing feature-based approaches to performance. With 92.10% accuracy, the SVM classifier yielded the best results.

Although they shared similar photographic patterns and symptoms, deep-learning feature-based methods could get the intricacies and features among several kinds of chile pests and illnesses.

III. Proposed Methodology

A. Stage 1: Data acquisition

The process of creating or compiling leaf image data from numerous public domain pictures or creating a custom dataset by specifications is known as data acquisition. The publicly accessible dataset "Chili Plant Disease" used in this work contains 100 photos, one for each of the following categories: healthy, leaf-curl, leaf-spot, whitefly, and yellowish.

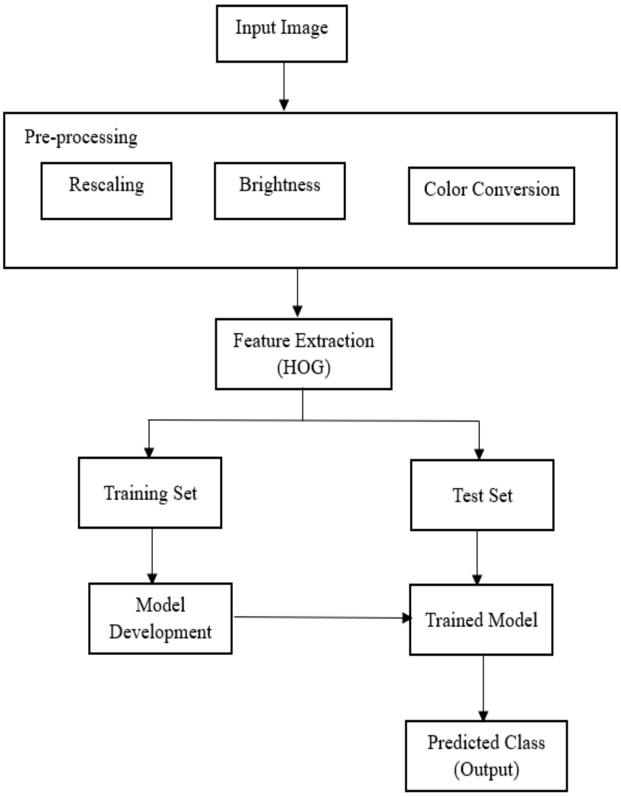

Fig. 1 Proposed methodology

B. Stage 2: Dataset

The Kaggle website's dataset is downloaded. This dataset is quite small—roughly 10 MB. The 100 photos in each class—healthy, leaf-curl, leaf-spot, whitefly, and yellowish, respectively—that make up the publicly accessible dataset "Chili Plant Disease" are used in this study.

C. Stage 3: Image pre -process

a) Resize Image: The input size of the picture must match the picture size kept in the dataset for the classification to be completed. Consequently, the input photo needs to be shrunk to a predetermined size initially. Make the photo 128 × 64 pixels in size. Every picture input data is converted, for instance, from a huge size to a defined size in the dataset format.

b) Brightness: Some pictures have too much darkness. The brightness feature is used to adjust the pixel value to suit the needs.

c) RGB to grey image Conversion: In image analysis and computer vision applications, converting RGB to grayscale images is a typical pre-processing step. It entails transforming an RGB (Red, Green, and Blue) color photo into a gray-scale photo with a single intensity value channel. The following are the procedures needed to translate an RGB photo to a gray-scale photo: 1. Open the RGB file: Typically, a 3-dimensional array of pixel values is used to depict an RGB image, with each pixel holding three values for the red, green, and blue color channels. 2. get grayscale values: The weighted sum of the red, green, and blue color channels is used to find the gray-scale number for each pixel in the image. The luminosity approach, which weights the channels based on how bright they are judged to be, is one popular formula for this: gray is equal to 0.0722 * B + 0.7152 * G + 0.2126 * R. 3. Produce the image in grayscale: A new 2-dimensional array that represents the gray image is made using the grayscale values that were computed in the second phase. There is just one channel of intensity values in the array, and they range from 0 (black) to 255 (white). 4. Show the gray image: A grayscale color map, with deeper gray tones denoting lower intensity values and lighter gray tones denoting greater intensity values, can be used to display the gray image.

Because it lowers the dimensionality of the image and eliminates color information that might not be pertinent to the work at hand, RGB to grayscale image conversion helps to streamline image processing tasks like segmentation, information extraction, and categorization. The next stage is feature extraction, which in this case is done using the appropriate feature extraction approach (HOG).

D. Stage 4: Feature Extraction HOG

In 2005, B. Triggs and N. Dalal invented the Histogram-of-Oriented-Gradients (HOG) characteristics. An information descriptor called Histogram-of-Oriented-Gradients (HOG) is used in picture processing, mostly for object discovery and information extraction from images. The pedestrian detection algorithm uses the HOG feature descriptor, which is calculated on a 64x128 cover of a photo. A photo can be any size [28]. Usually, several picture positions are examined for covers at different scales. The static aspect ratio of the covers under investigation is the one constraint.

The patches in this instance must have a 1:2 aspect ratio. They can be 100×200, 128×256, or 1000×2000, for instance, but not 101×205. A big image measuring 720 by 475 pixels is displayed to demonstrate this point. In this study, a 100x200 patch has been chosen to calculate the HOG feature-descriptor. A photo is cropped and shrunk to 64 by 128 to create this patch. This picture patch now has a HOG description that can be computed.

An image with dimensions of width x height x 3 (channels) is typically converted to the information vector or array of size n by an information descriptor. The input picture for the HOG feature descriptor is 64 × 128 x 3, and the resultant information vector has a size of 3780. For tasks like object detection and image recognition, it is quite helpful. This technique produces a feature vector that is useful for a variety of research problems. It can also yield good results when fed into a classifier such as the Support-Vector-Machine (SVM), KNN, or any other classifier.

The suggested approach's steps are as follows: 1.) Pre-processing, 2.) Gradient Image Calculation, 3.) Gradient Histogram Calculation in 8x8 Cells 4.) Block Normalization 16x16 5.) Determine the Oriented Gradients feature vector of histogram 6.) Create the training model via mean, and 7.) Use Euclidean Distance to evaluate the pre-trained model.

E. Step 5: Calculate the Gradient Images

Since the histogram of gradients can be calculated, the horizontal and vertical gradients must be calculated before the HOG descriptor can be computed. This can be easily accomplished by using kernels to filter the image [29].

F. Step 6: Calculate Histogram of Gradients in 8×8 cells

It involves partitioning the picture into 8x8 cells and computing a gradient histogram for each of those cells.

G. Step 7: 16×16 Block Normalization

Larger blocks are created by grouping adjacent cells, and these blocks are then normalized to lessen the impact of changes in lighting and contrast. L2-norm is a popular normalizing technique that divides each cell's gradient vector by the block's L2-norm.

H. Step 8: Calculate the Histogram of Oriented Gradients feature vector

It will have a total of 7 x 15 = 105 positions, with 7 straight and 15 perpendicular positions. A 36×1 vector is used to denote each 16 × 16 cells. Finally, it will generate a 36 × 105 = 3780-dimensional feature when it is integrated into a giant vector.

I. Stage 9: Training with Euclidean distance mean

Every class image's HOG feature is computed and saved as a .csv file. Each feature in an image has a vector length of 3780 feature points. The mean value of each column is computed for every 100 photos in each class. Every hog feature that deviates from the mean point is transformed using the boundary point that has been determined through a series of studies. That far point is regarded as an anomaly. The mean vector for each class is computed. Consequently, there is a single mean vector with a length of 3780 for every class. Rather than using 100 photos to represent each class, just one mean vector is used.

A mean vector, sometimes referred to as a center feature vector or representative feature vector, is a representation of 100 images in the same class. In this research effort, those five mean vectors are taken into consideration as a model.

J. Stage 10 Test with pre-training Euclidean Distance

When the proposed system is tested with an unknown sample, it will identify the hog traits just like it would with training data. Thus, using the hog technique, the test sample's feature length is likewise 3780. It is determined how far apart the test sample feature vector's Euclidean distance is from the class mean feature vector. The test sample with the least distance from those mean vectors receives the class label.

IV. EXPERIMENTS AND RESULTS

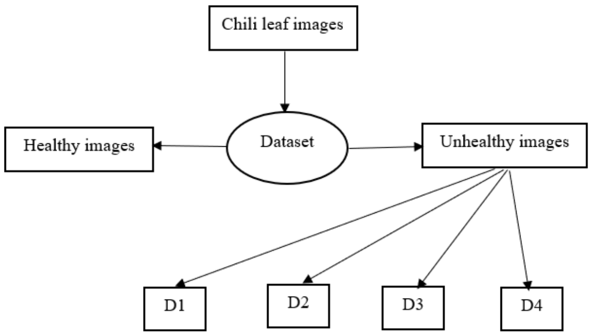

Fig. 2 Chili Disease Experiment Structure

The dataset has been divided into two halves, as illustrated in Figure 2 above. A portion of the image is healthy, whereas the other portion is unhealthy. There are numerous categories within the harmful section. There are five class designations in all in this study. Healthy, leaf-curl, leaf-spot, whitefly, and yellowish are the names of the class labels.

Table 1: Accuracy of existing work using deep learning

Sr No	Disease	Accuracy
1	Healthy	80%
2	Leaf curl	100%
3	Leaf spot	90%
4	Whitefly	80%
5	Yellowish	70%
	Average:	**84%**

Table 2 Comparison of results with different outlier values

Disease type	**Outlier value (Replacement value)**		
	(0.025) 0.0016	**(0.0016) 0.00125**	**(0.00125) 0.009**
Healthy	59%	63%	75%
Leaf curl	85%	94%	93%
Leaf spot	57%	74%	83%
Whitefly	56%	70%	81%
Yellowish	51%	65%	73%
Average:	**62%**	**73%**	**81%**

The proposed work with Euclidean distance from the mean with different outlier values, the outlier value 0.00125 with the replacement value (boundary point) 0.009 gives a high accuracy of 81.00%.

V. CONCLUSION AND FUTURE WORK

This method looks for the disease type in the chili leaves. This method makes use of scaling and color conversion during pre-processing. The following stage involves extracting the features from the previously processed photo using the Histogram-of-Gradients technique. The mean representative is computed as part of the categorization process once the hog features have been extracted. The model is tested using the Euclidean distance between the mean representative and the unknown sample. The feature that deviates from the mean is transformed into the pre-defined border point in this approach.

A distance of more than 0.0025 with the converted boundary point as 0.0016 gave an average accuracy rate of 61.6%. A distance of more than 0.0016 with the converted boundary point as 0.00125 gave an average accuracy rate of 73.2%. A distance of more than 0.00125 with the converted boundary point as 0.0009 gave an average accuracy rate of 81.0%. It has been observed that the disease type is recognized with an accuracy rate of 81% when the outlier is considered at the distance 0.00125 and converted with the almost mean value.

This approach is implemented to identify four types of chili leaf disease leaf-curl, leaf-spot, whitefly, and yellowish with a recognition rate of 81%. In the future, it can be extended to recognize a greater number of chili leaf disease types with higher accuracy.

REFERENCES

[1] Fuentes, A., Yoon, S., Youngki, H., Lee, Y., & Park, D.S. (2016). Characteristics of Tomato Plant Diseases—A study for tomato plant disease identification. *Proc. Int. Symp. Inf. Technol. Converg*, 1, 226–231.

[2] Ahmed, K., Shahidi, T. R., IrfanulAlam, S. M., & Momen, S. (2019). Rice leaf disease detection using machine learning techniques. *Int. Conf. Sustain. Technol. Ind.* 4.0, STI 2019, vol. 0, pp. 1–5, DOI:10.1109/STI47673.2019.9068096.

[3] Albayrak, A., Çeven, S., & Bayır, R. (2021). Modeling of migratory beekeeper behaviors with machine learning approach using meteorological and environmental variables: The case of Turkey. *Ecological Informatics*, 66, 101470.

[4] S. K. Baduguw R. K. Kontham, V. K. Vakulabharanam, and B. Prajna, "Calculation of Texture Features for Polluted Leaves," Int. J. Sci. Res. Comput. Sci. Eng., vol. 6, no. 1, pp. 11–21, 2018, doi:10.26438/ijsrcse/v6i1.1121.

[5] Tete, T. N., & Kamlu, S. (2017). Plant Disease Detection Using Different Algorithms. *Proc. Second Int. Conf. Res. Intell. Comput. Eng.*, vol. 10, pp. 103–106, DOI: 10.15439/2017r24.

[6] Girshick, R. (2017) Food and Agriculture Organization of the United Nations. Plant Pests and Diseases. Available online: http:// www.fao. org/emergencies/emergency-types/plant- pests-and-diseases/en/ (accessed on 20 June 2017)., Fast R-CNN. in *2015 IEEE International Conference on Computer Vision (ICCV)*, Santiago, 2015.

[7] Girshick, R. J. (2017). Food and Agriculture Organization of the United Nations. Plant Pests and Diseases. 2017. Available online: http:// www. fao. org/emergencies/emergency-types/plant- pests-and-diseases/ en/ (accessed on 20 June 2017).

[8] Shi, Y., Wang, X. F., Zhang, S. W., & Zhang, C. L. (2015). PNN based crop disease recognition with leaf image features and meteorological data. *Int. J. Agric. Biol. Eng.*, vol. 8, no. 4, pp. 60–68, doi:10.3965/j.ijabe.20150804.1719.

[9] Rothe, P. R., & Kshirsagar, R. V. (2015). Cotton leaf disease identification using pattern recognition techniques. *2015 Int. Conf. Pervasive Comput. Adv. Commun. Technol. Appl. Soc. ICPC 2015*, vol. 00, no. C, DOI:10.1109/PERVASIVE.2015.7086983.

[10] Tm, P., Pranathi, A., Saiashritha, K., Chittaragi, N. B., & Koolagudi, S. G. (2018). Tomato Leaf Disease Detection Using Convolutional Neural Networks. *2018 11th Int. Conf. Contemp. Comput. IC3 2018*, pp. 2–4, DOI: 10.1109/IC3.2018.8530532.

[11] Patil, A., Lad, K. (2021). Chili Plant Leaf Disease Detection Using SVM and KNN Classification. *In: Rathore, V.S., Dey, N., Piuri, V., Babo, R., Polkowski, Z., Tavares, J.M.R.S. (eds) Rising Threats in Expert Applications and Solutions. Advances in Intelligent Systems and Computing*, vol 1187. Springer, Singapore. https://doi.org/10.1007/978-981-15-6014-9_26

[12] Radha, S. (2017). Leaf Disease Detection Using Image Processing for Pesticides Spraying. *Int. J. Adv. Eng. Res.Dev.*, vol. 4, no. 04, DOI:10.21090/ijaerd.60415.

[13] Seelam, & Roy S. A. (2023). Comparative Analytics on Chilli Plant Disease using Machine Learning Techniques. Electronic Theses and Dissertations. 2603.

[14] Singh, K., Chetia & M., Singh and Malti & S. (2017). Detection and Classification of Plant Leaf Diseases in Image Processing using MATLAB. *International Journal of Life sciences Research*, vol. 5, no. 1, pp. 120-124, 2017.

[15] Chauhan, R., Ghanshala, K. K., & Joshi, R. (2018). Convolutional neural network (CNN) for image detection and recognition. Paper presented at the *2018 first international conference on secure cyber computing and communication (ICSCCC).*

[16] Jayakumar, D., Elakkiya, A., Rajmohan, R., & Ramkumar, M. (2020). Automatic prediction and classification of diseases in melons using stacked RNN based deep learning model. *Paper presented at the 2020 international conference on system, computation, automation and networking (ICSCAN).* 82

[17] Karthik, R., Hariharan, M., Anand, S., Mathikshara, P., Johnson, A., & Menaka, R. (2020). Attention embedded residual CNN for disease detection in tomato leaves. *Applied Soft Computing*, 86, 10593

[18] Wang, H., Pang, D., & Ma, J. (2022). Combining CNN and MLP for Plant Pathology Recognition in Natural Scenes. *Paper presented at the 2022 IEEE International Symposium on Circuits and Systems (ISCAS).*

[19] Shi, Wang, Y., X. F., Zhang, S. W., & Zhang, C. L. (2015). PNN based crop disease recognition with leaf image features and meteorological data. *Int. J. Agric. Biol. Eng.*, vol. 8, no. 4, pp. 60–68, 2015, doi:10.3965/j.ijabe.20150804.1719.

[20] Araujo, S. D. C. S., Malemath, Dr. V. S., & Sundaram, Dr. K. M. (2019). Disease Identification in Chilli Leaves using Machine Learning Techniques. *In International Journal of Engineering and Advanced Technology* (Vol. 9, Issue 1s3, pp. 325–329). *Blue Eyes Intelligence Engineering and Sciences Engineering and Sciences Publication - BEIESP.* https://doi.org/10.35940/ijeat.a1061.1291s319

[21] Fuentes, A., Yoon, S., Youngki, H., Lee, Y., & Park, D.S. (2016). Characteristics of Tomato Plant Diseases—A study for tomato plant disease identification. *Proc. Int. Symp. Inf. Technol.Converg.* 1, 226–231

[22] Gilbertson, R.L., Batuman, O. (2013). Emerging Viral and Other Diseases of Processing Tomatoes: Biology Diagnosis and Management. Acta Hortic. 1, 35–48. [CrossRef]

[23] Das Chagas Silva Araujo, S., Malemath, V. S., & Sundaram, K. M. (2021). Symptom-Based Identification of G-4 Chili Leaf Diseases Based on Rotation Invariant. *In Frontiers in Robotics and AI* (Vol. 8). Frontiers Media SA. https://doi.org/10.3389/frobt.2021.650134

[24] Vinoth Kumar, K., & Jayasankar, T. (2019). An identification of crop disease using image segmentation. *Int J Pharm Sci Res*, vol. 10, no. 3, pp. 1054–1064, 2019, DOI: 10.13040/IJPSR.0975-8232.10(3).1054-64.

[25] Coakley, S.M., Scherm, H., Chakraborty, S. (2019). Climate Change and Plant Disease Management. *Annu. Rev. Phytopathol*. 1999,37, 399–426. [CrossRef] [PubMed]International Journal of Engineering Science and Computing, May 2019 22335 http://ijesc.org/

[26] Ahmad L. N., Mohd Noor M. R., & Chang S. W. (2021). Integrated analysis of machine learning and deep learning in chili pest and disease identification. *J Sci Food Agric.* 2021 Jul;101(9):3582-3594. doi: 10.1002/jsfa.10987. Epub 2020 Dec 24. PMID: 33275806.

[27] Jagadeesh D. P., Rajesh Y., & Abdulmunaf S.B. (2023). Statistical Methods for Quantitatively Detecting Fungal Disease from Fruits. *International Journal of Intelligent Systems and Applications in Equ 4 Engineering*, ISSN:2147-67992.

[28] Sufola D. C., & Meenakshi S. K. (2016). Vegetable- Fruit Identification Based on Intensity and Texture Segmentation. in special issue of SCOPUS INDEX JOURNAL titled *International Journal of Control Theory and Applications (2016)*.(ISSN : 0974-5572), 12th October 2016.

[29] Lecun, Y., Bottou, L. & Haffner, Y. B. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, Nov 1998.

[30] Jayanthi M. G., & Shashikumar D. R. (2020). Automatic Tomato Plant Leaf Disease Classification using Multi-Kernel Support Vector Machine. *Int. J. Eng. Adv. Technol.*, vol. 9, no. 5, pp. 560–565, 2020, DOI:10.35940/ijeat.e9689.069520.

[31] Website (2023). https://digitalcommons.georgiasouthern.edu/etd/2603.