An experimental study of tomato viral leaf diseases detection using machine learning classification techniques

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ABSTRACT

Agriculture is the backbone of India and more than 50% of the population is dependent on it. With the increasing demand for food with the increase in population, it is the need of time that crops should be prevented against diseases. More than 1K acres of land with tomato diseases got affected in Pune only during this pandemic (2021). It could have been prevented by correct identification of the disease and then by corrective measures. This paper presents the experimental and comparative study of tomato leaf disease classification using various traditional machine learning algorithms like random forest (RF), support vector machines (SVM), naïve bayes (NB), and deep learning convolutional neural network (CNN) algorithm. In this study, it is perceived that CNN with a pre-trained Inception v3 model was able to detect and classify better than traditional methods with more than 95% accuracy.

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1. INTRODUCTION

Tomato is a plant that is consumed in varied varieties all over the world like vegetable curries, jams, sauces, chutneys, salads, and drinks. India ranks second [1] in the global tally in tomato production but the yield it gets per hectare is very less than compared to other countries. The reason behind it is that the tomato crop in India gets affected by bacterial diseases (wilt, early blight) and leaf curl virus which causes a loss of up to 70-100% of production (Indian Institute of Horticultural Research) [1]. Various institutes are trying to bring hybrid disease-resistant varieties to solve the problem, but they all are very time-consuming and costly affairs. With the advancement of technology, we can get better solutions like the prediction of diseases at early stages and correct remedy at the appropriate time can save a huge production. In India the major states producing tomatoes are shown in Figure 1: in the northern region are Bihar, Uttar Pradesh, in the western region: in Maharashtra, in the southern region are Karnataka, Andhra Pradesh, in the eastern region, is Assam, Orissa, and in the central region is Madhya Pradesh [2].

Generally, tomato is known as a warm season crop that could give the best quality at a temperature between 21-24 ^{o}C. Temperature above 30 ^{o}C and frost and humidity affect the plant tissues which results in the development of various fungal, bacterial, or viral diseases, hence, detection of crop disease at an early stage is a research area. The major diseases of tomato that affect the crop are given in Figure 2.

The farmers detect the disease by looking at the parts of the crop with naked eyes (which requires expertise) or they send the sample to the centers for testing (time-consuming). Few techniques that are used to detect crop diseases are thermography (use to detect the change in the surface temperature due to reduction in transpiration and the limitation is not able to detect identify/the disease type), fluorescence (uses the method to measure the change in photosynthetic activity and chlorophyll for detection of the pathogen, and the drawback is that is of limited practical use), gas chromatography (uses volatile organic compounds to detect the nature and type of infection and the disadvantage of this method is the lack of pre-collected sample of VOC's). So, the better option is the use of technology through machine learning algorithms.

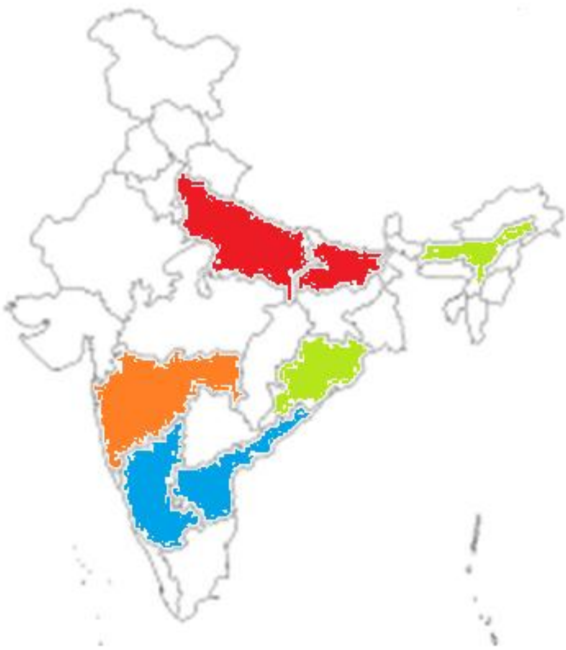

Figure 1. Major states in India produce tomatoes [2]

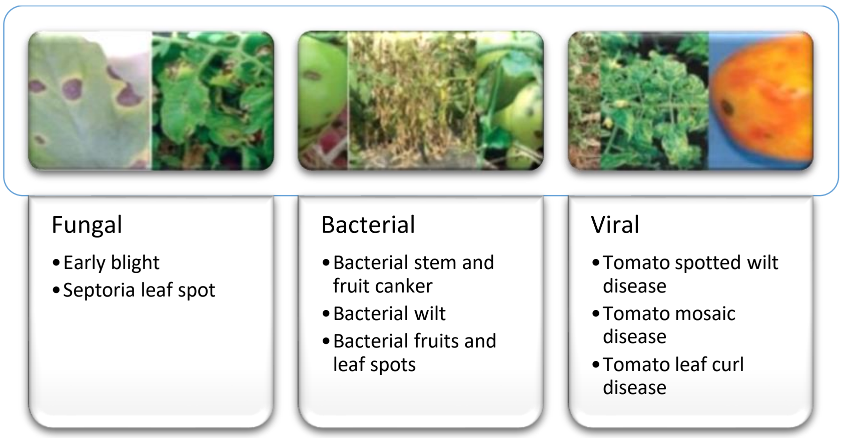

Figure 2. Sample of major diseases of tomato in India (NHB, India database)

Several studies were done earlier that show the capability of technology using algorithms of machine learning to identify objects in various sectors like retail, human behavior, face recognition [3], facial expressions [4], handwriting recognition [5], intrusion detection [6], movie recommendation [7], and food segmentation [8]. The health sector is also using it to identify/detect/predict various diseases like diabetes prediction, cancer detection [9], [10], heart disease, skin problems, Parkison's disease identification [11], COVID-19 from chest X-rays [12], and many more. The crop disease classification can also be done efficiently and effectively using machine learning. We discovered in our study that various machine learning algorithms are applied to various categories of agriculture finding the deficiency of nutrients in maize [13], and groundnut leaf disease detection using convolutional neural network (CNN) and bag of features (BOF) with speeded-up robust feature (SURF) [14].

While this study, we found that machine learning algorithms can be applied to identify tomato leaf diseases. Support vector machines (SVM) algorithm was used to identify black spots, cankers, and melanose by extracting the color, shape, and texture features, and segmentation was used to detect the diseases [15]. PCA and one hot encoding were used by Reddy and an accuracy of more than 85% was achieved [16]. The various data augmentation techniques like contrast, random zoom, and crop, the central zoom was used to identify early and late blight, and leaf mold diseases with the CNN 5-fold cross-validation algorithm was used and an accuracy of 98% was achieved [17]. LabelImg tool was used to annotate the images with faster region (RCNN) with ResNet 50 used to achieve an average accuracy of 81% for early blight, leaf curl, Septoria, and bacterial leaf spot diseases [18]. A CNN with 8 hidden layers was used and an accuracy of 98.4% accuracy was achieved [19]. Pre-processing methods like image flip horizontal, and rotations were used to increase the data 6 times was used and a comparative study of MobileNetV2, Xception, and MobileNetV3 proved that NetMobile was better among them [20]. YoloV3 was improved by using 53 layers of convolutions and 5 layers of max pooling and an accuracy of more than 92% was achieved [21]. Early and late blight, leaf mold, bacterial leaf spot, and yellow leaf curl diseases were studied in China using ABCK [22]. Early blight, bacterial spot, septoria leaf spot; iron chlirosis were studied a few years back with 100% accuracy in early blight [23]. Multiple linear regression method was used to detect the diseases [24]. Color descriptors and textures were used to extract the features and a comparative study of algorithms like KNN, ANN, random forest (RF), Naïve Bayes (NB), and SVM was done and found that RF has achieved better accuracy than others [25]. Color histograms, Hu moments, local binary pattern, and haralick features are used for testing and training purposes where RF and DT were used, and RF again has shown better accuracy [26]. Yolo model with a train-test split ratio of 90%-10% was used and an accuracy of 76% was achieved [27]. Features were extracted using image processing tools like contrast, energy, correlation, mean homogeneity, entropy, variance, standard deviation, root mean square, skewness, kurtosis, features extracted were divided into 5 subsets and then these vectors were and classified using back propagation NN [28]. Image sizes were changed, and the noise was filtered using the weiner filter technique. Segmentation was done using a modified K-means image segmentation algorithm. The features were extracted using contrast, energy, entropy, homogeneity, and, uniformity property from the image segmentation and the feature extraction method used was grey level co-occurrence matrix (GLCM). Leaves were classified using SVM and adaptive neuro-fuzzy inference system (ANFIS) [29]. Leaf curl virus affected 70% of crop [30], [31]. The approach of bayesian learning using probabilistic approach is used and found better results than other optimized models [32]. K-means algorithm is used to diagnose the infected areas in the leaves and then multi-SVM was used for classification [33]. Through the review, it is understood that the majority of the work is done with traditional algorithms of machine learning. We are trying to do a comparative study of traditional machine learning algorithms with deep learning CNN and trying to find out if deep CNN provides better results.

2. METHOD

2.1. Data collection

Data of tomato leaf images are collected from plant village, a publicly available repository. The following four categories of diseases are chosen for this study:

a. Tomato mosaic virus (TMV): 1,000 images of it were collected. During the pandemic, a huge tomato crop loss in Maharashtra (Pune, Nashik, Ahmednagar, Satara) happened due to tomato viral diseases, and farmers lost more than 60 percent of the crop [22]. This virus affects the various parts of the plant like fruit, stem, and leaves. The fruit might have a brown or yellow color with reduced size. On the stem, dark brown colored patches appeared, and the leaves become yellow and green with the appearance of mottled and a mosaic.

b. Tomato septoria leaf spot (TSLS): 1,771 images were collected. Irregular small or round spots are grey in the center and there are dark color margins on leaves. It generally affects the lower leaves of the plant. Flowers and stems are attacked sometimes, but the fruits are attacked rarely by this disease. Hence the name septoria leaf spot.

c. Tomato target spot (TTS): 1,404 images were collected. This disease is much prevalent in West Bengal mainly in the Gangetic alluvial region (Adam Kamei). Small dark to large light brown color lesions appears on leaves and fruits.

d. Tomato yellow leaf curl virus (TYLCV): 5,357 images were collected. This disease is more prevalent in Tamil Nadu in India. Major symptoms of this disease are curling of leaves, reduced leaf size, plant starts rolling down and new leaves exhibiting yellow color.

e. Tomato healthy leaves (TH): 1,591 were collected. Healthy leaves are medium-sized leaves with soft fuzz. Once the model will be trained with the above-mentioned diseases, then we can compare it with the healthy leaves and find out the accuracy of the model.

2.2. Image annotation

Images were annotated using the Image annotation tool and knowledge base of the above said five classes created. Image annotation tool helps to annotate or label the images. After annotation, the features of each image will be recognized by the machine learnig model.

2.3. Training

Machine learning training was done with an 80%-20% train-test split with the randomized stratified method. The training was done using the following algorithms:

a. Random forest with the following properties: i) no. of trees: 10, ii) split subsets greater than 5, and iii) repeat train/test: 10.
b. Naïve Bayes with 80%-20% train test split.
c. SVM with the following properties: i) regression loss epsilon=0.10, ii) the kernel used as RBF, and iii) iteration of operational parameters: 100, numerical tolerance: 0.0010.
d. CNN with pre-trained inception v3 model and the following properties: i) neurons in hidden layer: 100, ii) activation: ReLu, iii) solver: Adam, and iv) maximal number of Iterations with replicable training: 3,500.

2.4. Results

The evaluation results are mentioned below. In this subsection, it is observed that CNN has shown better results than others. The detailes are mentioned below:

a. Evaluation results

The evaluation results of the experiment are shown in Table 1. It could be seen that classification accuracy, precision, and F1 score are much higher in a NN as compared to SVM, RF, and NB.

Table 1. Experimental results

Model	AUC	CA	F1	Precision	Recall
SVM	0.997	0.963	0.963	0.963	0.963
RF	0.977	0.877	0.876	0.876	0.877
NN	0.999	0.981	0.981	0.981	0.981
NB	0.945	0.775	0.775	0.796	0.766

b. Confusion matrices

Let's see the confusion matrices of all the algorithms applied in this experimental study in the following tables. Table 2 shows the confusion matrix of RF. The RF has detected the diseases with the following accuracy as shown in Table 3. NB confusion matrix is shown in Table 4. NB has detected the diseases with the following accuracy as per Table 4 shown in Table 5. SVM confusion matrix results can be seen in Table 6. SVM has detected the diseases with the following accuracy as per Table 6 with the details shown in Table 7, and finally, the confusion matrix of CNN with Inception v3 model is seen in Table 8. CNN has detected the diseases with the following accuracy as given in Table 8 calculated and shown the results in Table 9. It is observed with the experiment that yellow leaf curl virus disease is classified more accurately by these algorithms as the data set for it was more as compared to others.

Table 2. Confusion matrix for RF

	TH	TMV	TSLS	TTS	TYLCV	∑
TH	2747	22	82	278	51	3180
TMV	66	1494	220	81	139	2000
TSLS	91	162	2816	274	197	3540
TTS	294	67	300	2022	127	2810
TYLCV	18	40	108	122	10432	10720
∑	3216	1785	3526	2777	10946	22250

Table 3. Disease accuracy % of RF

TH (%)	TMV (%)	TSLS (%)	TTS (%)	TYLCV (%)
86.3	74.7	79.54	71.96	97.31

Table 4. Confusion matrix for NB

	TH	TMV	TSLS	TTS	TYLCV	∑
TH	1976	139	161	873	31	3180
TMV	99	1563	214	86	38	2000
TSLS	214	432	2399	379	116	3540
TTS	384	115	245	2048	18	2810
TYLCV	142	446	575	506	9051	10720
∑	2815	2695	3594	3892	9254	22250

Table 5. Disease accuracy % of NB

TH (%)	TMV (%)	TSLS (%)	TTS (%)	TYLCV (%)
62.13	78.15	67.77	72.88	84.43

Table 6. Confusion matrix for SVM

	TH	TMV	TSLS	TTS	TYLCV	∑
TH	3051	5	8	116	0	3180
TMV	3	1911	67	5	14	2000
TSLS	14	61	3173	239	53	3540
TTS	42	17	97	2596	58	2810
TYLCV	0	6	8	20	10686	10720
∑	3110	2000	3353	2976	10811	22250

Table 7. Disease accuracy % of SVM

TH (%)	TMV (%)	TSLS (%)	TTS (%)	TYLCV (%)
95.94	95.5	89.63	92.38	99.68

Table 8. Confusion matrix of NN with Inception v3 model

	TH	TMV	TSLS	TTS	TYLCV	∑
TH	3136	6	2	35	1	3180
TMV	3	1963	16	3	15	2000
TSLS	9	36	3403	78	14	3540
TTS	48	7	81	2646	28	2810
TYLCV	1	7	7	28	10677	10720
∑	3197	2019	3509	2790	10735	22250

Table 9. Disease accuracy % of CNN

TH (%)	TMV (%)	TSLS (%)	TTS (%)	TYLCV (%)
98.61	98.15	96.13	94.16	99.59

c. Accuracy

The accuracy percentage of the experiment is given in Table 10. It is observed in the experiment that SVM has also shown acceptable accuracies, but for septoria leaf spot it is not able to diagnose it so accurately.

Table 10. Disease accuracy % of RF, NB, SVM, NN

Algorithm	TH (%)	TMV (%)	TSLS (%)	TTS (%)	TYLCV (%)
RF	86.4	74.7	79.54	71.95	97.31
NB	62.14	78.15	67.77	72.88	84.43
SVM	95.94	95.55	89.63	92.38	99.68
NN	98.61	98.15	96.13	94.16	99.59

d. ROC curve analysis

Receiver operating characteristic (ROC) curve is used to compare various classification models and to evaluate their accuracy. It's a 2-dimensional plot with the ratio of true positive rate (TPR) on the Y–axis and false positive rate (FPR) on the X-axis where:

$$TPR=\frac{TP}{TP+FN} \quad (1)$$

and

$$\text{FPR}=\frac{FP}{FP+TN} \quad (2)$$

The area under the curve (AUC) gives the analytical computation comparing the accuracy of the classification models under consideration. The classifier having the greatest AUC is preferable. Figure 3 shows the classifiers list. The ROC curves are shown in Figure 4 (TH), Figure 5 (TMV), Figure 6 (TSLS), Figure 7 (TTS), and Figure 8 (TYLCV). Here, it is observed that CNN has more AUC than compared to other models.

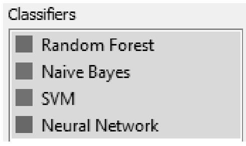

Figure 3. Classifiers list

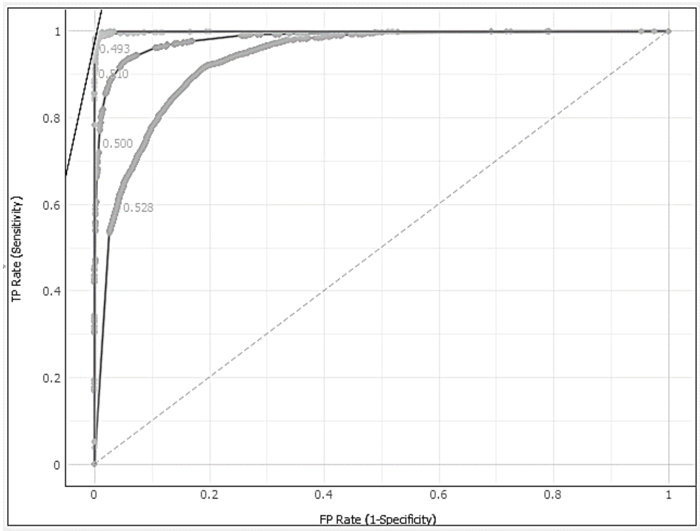

Figure 4. ROC curve of tomato healthy

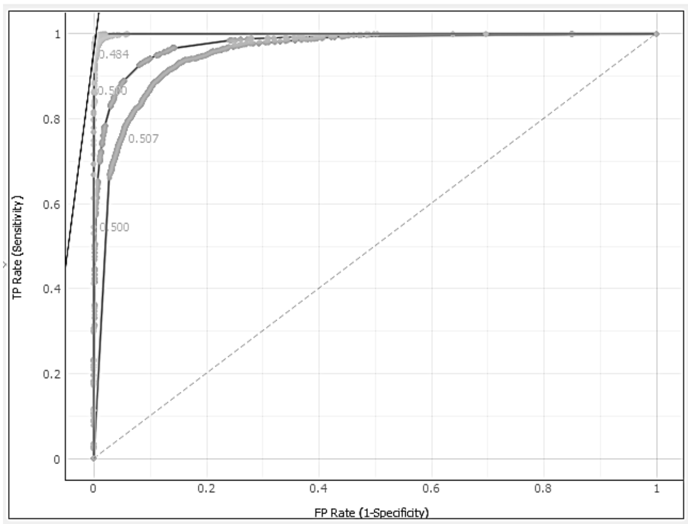

Figure 5. ROC curve of TMV

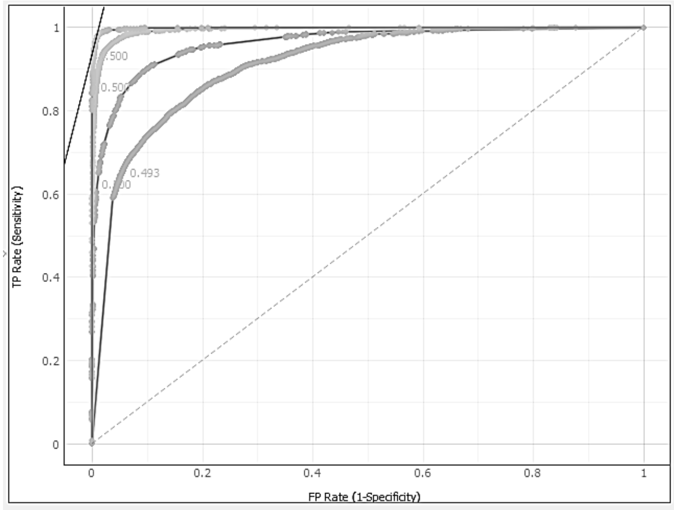

Figure 6. ROC curve of TSLS

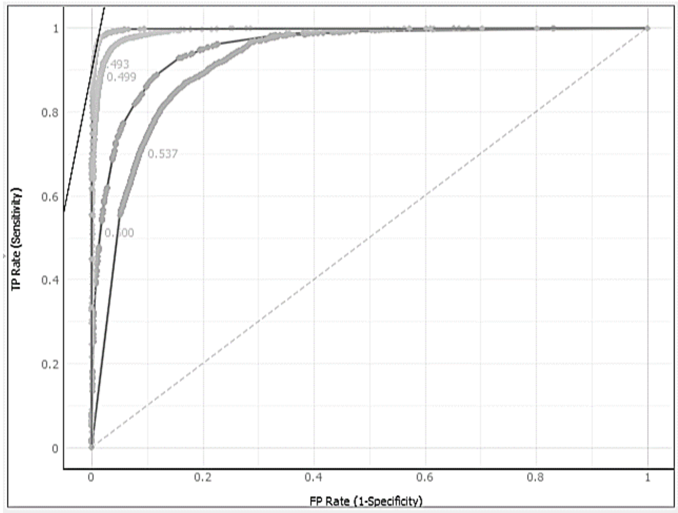

Figure 7. ROC curve of TTS

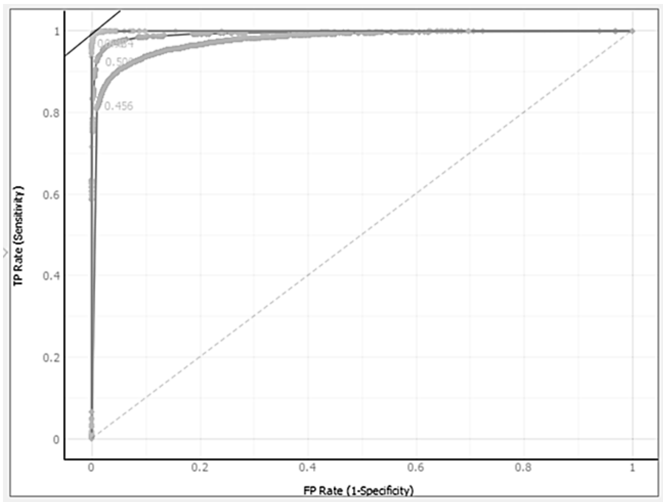

Figure 8. ROC curve of TYLCV

e. Samples of misclassified

Figures 9-13 shows the misclassified samples of TH, TMV, TSLS, TTS, and TYLCV. It is observed that TSLS and TTS are misclassified more as compared to TMV and TYLCV. TSLS is majorly misclassified as TTS and vice versa. In the future, this could be reduced by using image processing techniques and by increasing the data set for TSLS, TTS, and TMS.

Figure 9. Sample of TH misclassified

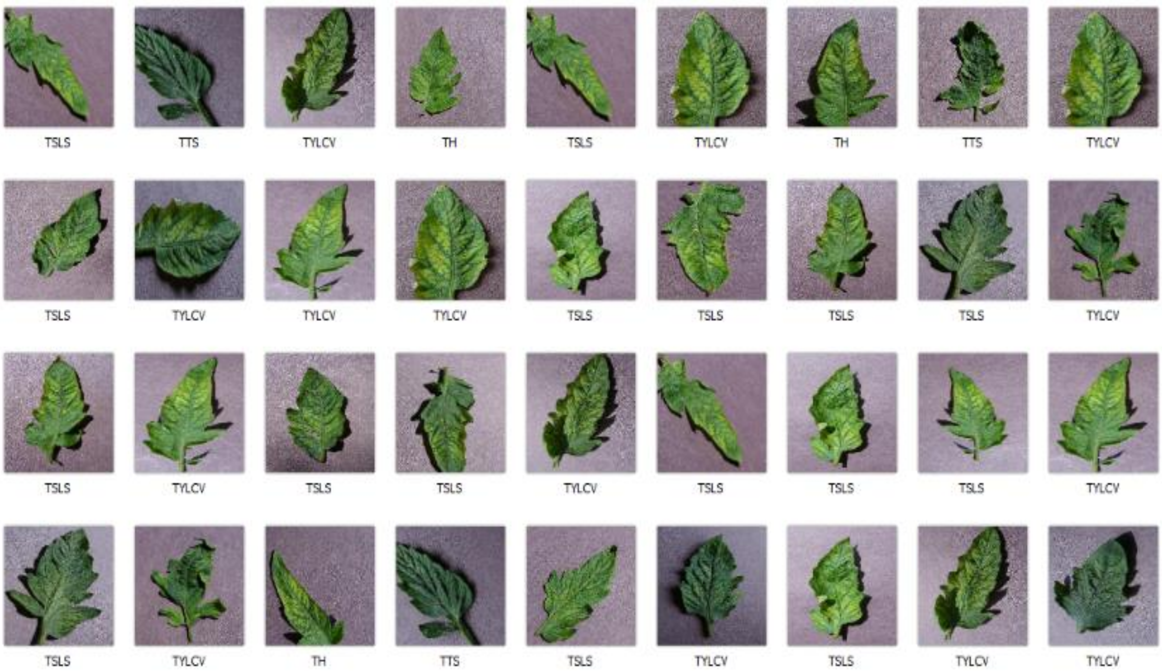

Figure 10. Sample of TMV leaves misclassified

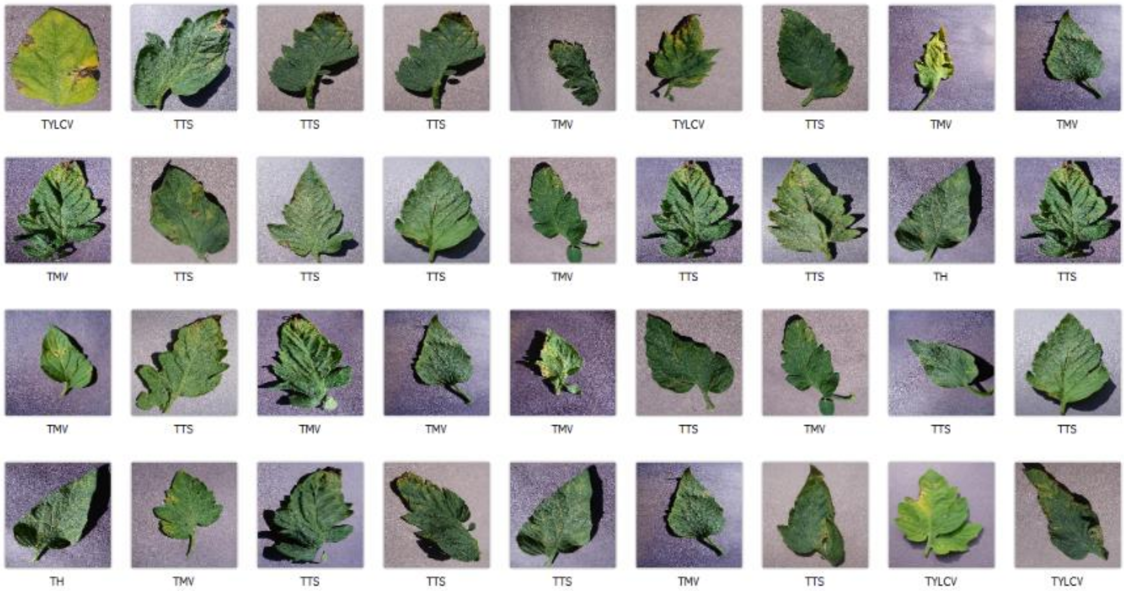

Figure 11. Sample of TSLS leaves misclassified

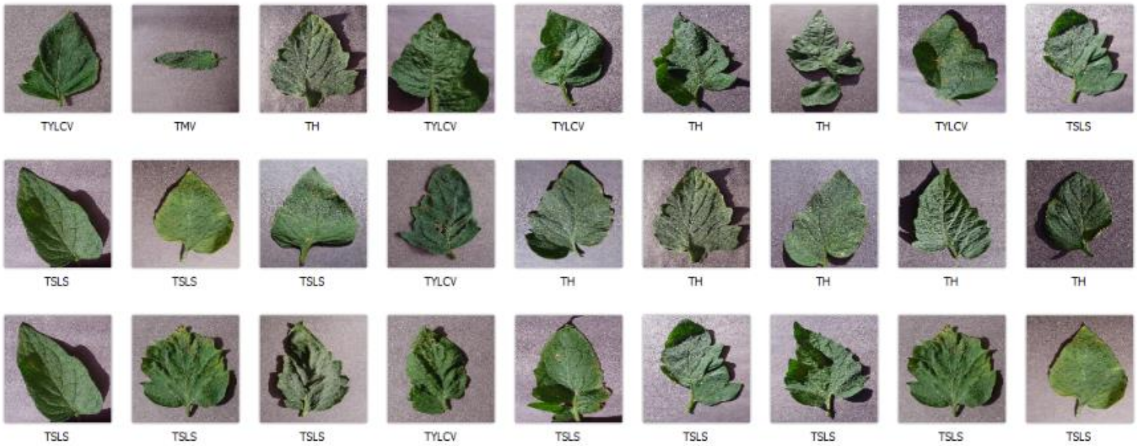

Figure 12. Sample of TTS leaves misclassified

Figure 13. Sample of TYLCV misclassified

3. CONCLUSION

A comparative experimental study is done for four machine learning algorithms namely SVM, NB, RF, and CNN for four tomato disease detection that is TMV, TTS, TYLCV, and TSLS. SVM, RF, FFNN, and NB were used by many authors. Many classification techniques were observed, and they performed in a a different form for different datasets when applied to different tools. All classification techniques have some pros and cons when applied to classify diseases. The result of this experiment shows that deep learning methods CNN and its variants detect crop diseases with more accuracy. In the future, deep CNN with Image processing techniques can be explored to detect the diseases and then compared with other classification methods. Also, a comparative study of various deep CNN can be done.

REFERENCES

[1] S. Agarwal, S. P. Rao, and V. Dhar, "Horticultural Statistics at a Glance 2018," *Government of India: Controller of Publication*, Nov. 2018.

[2] N. Madhumurthy and M. Sundaramoorthy, "A Report on the study of tomato value chain and its financing," *College of Agricultural Banking: Reserve Bank of India Pune*, 2018.

[3] A. Herlambang, P. W. Buana, and I. N. Piarsa, "Cloud-based architecture for face identification with deep learning using convolutional neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 2, p. 811, Aug. 2021, doi: 10.11591/ijeecs.v23.i2.pp811-820.

[4] A. Dixit and T. Kasbe, "Multi-feature based automatic facial expression recognition using deep convolutional neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, p. 1406, Mar. 2022, doi: 10.11591/ijeecs.v25.i3.pp1406-1419.

[5] S. Ahsan, S. T. Nawaz, T. B. Sarwar, M. S. U. Miah, and A. Bhowmik, "A machine learning approach for Bengali handwritten vowel character recognition," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 11, no. 3, p. 1143, Sep. 2022, doi: 10.11591/ijai.v11.i3.pp1143-1152.

[6] A. M. Bamhdi, I. Abrar, and F. Masoodi, "An ensemble based approach for effective intrusion detection using majority voting," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 19, no. 2, pp. 664-671, Apr. 2021, doi: 10.12928/telkomnika.v19i2.18325.

[7] D. K. Behera, M. Das, S. Swetanisha, and P. K. Sethy, "Hybrid model for movie recommendation system using content K-nearest neighbors and restricted Boltzmann machine," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 1, pp. 445-452, Jul. 2021, doi: 10.11591/ijeecs.v23.i1.pp445-452.

[8] J. O. P.-Arenas, R. J.-Moreno, and C. G. P.-Suescún, "ResSeg: Residual encoder-decoder convolutional neural network for food segmentation," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 1, pp. 1017 -1026, Feb. 2020, doi: 10.11591/ijece.v10i1.pp1017-1026.

[9] J. E. Aurelia, Z. Rustam, and I. Wirasati, "Cervical cancer classification using convolutional neural network-support vector machine," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 19, no. 5, pp. 1605-1611, Oct. 2021, doi: 10.12928/telkomnika.v19i5.20406.

[10] S. Kothari, S. Chiwhane, S. Jain, and M. Baghel, "Cancerous brain tumor detection using hybrid deep learning framework," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 26, no. 3, pp. 1651-1661, Jun. 2022, doi: 10.11591/ijeecs.v26.i3.pp1651-1661.

[11] N. Benayad, Z. Soumaya, B. D. Taoufiq, and A. Abdelkrim, "Features selection by genetic algorithm optimization with k-nearest neighbour and learning ensemble to predict Parkinson disease," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 2, pp. 1982-1989, Apr. 2022, doi: 10.11591/ijece.v12i2.pp1982-1989.

[12] F.-Z. Hamlili, M. Beladgham, M. Khelifi, and A. Bouida, "Transfer learning with Resnet-50 for detecting COVID-19 in chest X-ray images," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, pp. 1458 -1468, Mar. 2022, doi: 10.11591/ijeecs.v25.i3.pp1458-1468.

[13] N. Sabri, N. S. Kassim, S. Ibrahim, R. Roslan, N. N. A. Mangshor, and Z. Ibrahim, "Nutrient deficiency detection in Maize (Zea mays L.) leaves using image processing," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 9, no. 2, pp. 304-309, Jun. 2020, doi: 10.11591/ijai.v9.i2.pp304-309.

[14] H. H. Hamzah, N. Sabri, Z. Ibrahim, and D. Isa, "Convolutional neural network vs bag of features for bambara groundnut leaf disease recognition," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 14, no. 1, pp. 368-374, Apr. 2019, doi: 10.11591/ijeecs.v14.i1.pp368-374.

[15] S. D. Kumar, S. Esakkirajan, S. Bama, and B. Keerthiveena, "A microcontroller based machine vision approach for tomato grading and sorting using SVM classifier," *Microprocessors and Microsystems*, vol. 76, p. 103090, Jul. 2020, doi: 10.1016/j.micpro.2020.103090.

[16] T. R. Gadekallu *et al.*, "A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU," *Journal of Real-Time Image Processing*, vol. 18, no. 4, pp. 1383–1396, Jun. 2020, doi: 10.1007/s11554-020-00987-8.

[17] K. R, H. M, S. Anand, P. Mathikshara, A. Johnson, and M. R, "Attention embedded residual CNN for disease detection in tomato leaves," *Applied Soft Computing*, vol. 86, p. 105933, Jan. 2020, doi: 10.1016/j.asoc.2019.105933.

[18] D. V. A. Natarajan, M. M. Babitha, and D. M. S. Kumar, "Detection of disease in tomato plant using Deep Learning Techniques," *International Journal of Modern Agriculture*, vol. 9, no. 4, Dec. 2020.

[19] M. Agarwal, S. K. Gupta, and K. K. Biswas, "Development of Efficient CNN model for Tomato crop disease identification," *Sustainable Computing: Informatics and Systems*, vol. 28, p. 100407, Dec. 2020, doi: 10.1016/j.suscom.2020.100407.

[20] V. G.-Huitron, J. A. L.-Borges, A. E. R.-Mata, L. E. A.-Sosa, B. R.-Pereda, and H. Rodriguez, "Disease detection in tomato leaves via CNN with lightweight architectures implemented in Raspberry Pi 4," *Computers and Electronics in Agriculture*, vol. 181, p. 105951, Feb. 2021, doi: 10.1016/j.compag.2020.105951.

[21] J. Liu and X. Wang, "Early recognition of tomato gray leaf spot disease based on MobileNetv2-YOLOv3 model," *Plant Methods*, vol. 16, no. 1, Jun. 2020, doi: 10.1186/s13007-020-00624-2.

[22] X. Chen, G. Zhou, A. Chen, J. Yi, W. Zhang, and Y. Hu, "Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet," *Computers and Electronics in Agriculture*, vol. 178, p. 105730, Nov. 2020, doi: 10.1016/j.compag.2020.105730.
[23] S. Vetal and R. Khule, "Tomato Plant Disease Detection using Image Processing," *IJARCCE*, vol. 6, no. 6, pp. 293–297, Jun. 2017, doi: 10.17148/ijarcce.2017.6651.
[24] G. Sun, X. Jia, and T. Geng, "Plant Diseases Recognition Based on Image Processing Technology," *Journal of Electrical and Computer Engineering*, vol. 2018, pp. 1–7, 2018, doi: 10.1155/2018/6070129.
[25] B. L.-Benoso, J. C. M.-Perales, and J. C.-Galicia, "Tomato disease detection by means of pattern recognition," *International Journal of Computing and Optimization*, vol. 7, no. 1, pp. 35–45, 2020, doi: 10.12988/ijco.2020.9823.
[26] J. Basavaiah and A. A. Anthony, "Tomato Leaf Disease Classification using Multiple Feature Extraction Techniques," *Wireless Personal Communications*, vol. 115, no. 1, pp. 633–651, Jun. 2020, doi: 10.1007/s11277-020-07590-x.
[27] M. Patil, G. Langar, P. Jain, and N. Panchal, "Tomato leaf disease detection using artificial intelligence and machine learning," *International journal of advance scientific research and engineering trends*, vol. 5, no. 7, pp. 1–5, Jul. 2020.
[28] R. Gupta and T. Verma, "Tomato Leaf Disease Detection using Back Propagation Neural Network," *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, no. 8, pp. 529–538, Jun. 2020, doi: 10.35940/ijitee.h6531.069820.
[29] S. Sivagami and S. Mohanapriya, "Tomato leaf disease detection using image processing technique," *International Journal of Agricultural Technology*, vol. 17, no. 3, pp. 1135–1146, 2021.
[30] "Now there's another virus in Maharashtra, and it's destroying the tomato crop," May 23, 2020. [online], Available at: https://theprint.in/india/now-theres-another-virus-in-maharashtra-and-its-destroying-the-tomato-crop/427475/
[31] "IIHR report finds a plethora of viruses behind tomato crop loss in state | Cities News, The Indian Express," May 22, 2020, [online], Available at: https://indianexpress.com/article/cities/pune/iihr-report-finds-a-plethora-of-viruses-behind-tomato-crop-loss-in-state-6422937/
[32] S. Hernández and J. L. López, "Uncertainty quantification for plant disease detection using Bayesian deep learning," *Applied Soft Computing*, vol. 96, p. 106597, Nov. 2020, doi: 10.1016/j.asoc.2020.106597.
[33] R. Agrawal, "Healthy leaves Identification using Multi SVM Approach," *International Journal of Advanced Science and Technology*, vol. 29, no. 3, Mar. 2020.

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