Tomato Plant Disease Classification Using Local Patterns

Megha AGARWAL [1]

[1]Department of Electronics and Communication Engineering, Jaypee Institute of Information Technology, Noida, India

drmegha.iit@gmail.com

DOI: 10.15598/aeee.v21i4.5036

Article history: Received Jan 19, 2023; Revised Aug 13, 2023; Accepted Oct 15, 2023; Published Dec 31, 2023.

Abstract. *Agricultural sector has significant impact on the people health and on the economy of the world. Climate variation is important reason in causing plant diseases hence, affecting the estimated crop production. Prior detection of plant diseases is utmost important for improving the quality and quantity of production within the due course of time. In this paper, this challenge is addressed by automatically detecting tomato diseases from the hand-crafted features extracted from the plant leaves and machine learning classifiers. Different frequency bands are extracted using Gaussian filters and local statistics of leaves are captured using patterns to design frequency decomposed local ternary pattern (FDLTP). It provides a fast and accurate solution to avoid uncertainty in the farm production. Benchmarked dataset of Taiwan tomato leaves is used to verify the results. Performance of machine learning classifiers as well as deep learning solutions are compared, and 95.6% accuracy is obtained using proposed feature along with k-nearest neighbor classifier. It is a quick and easy to deploy method for real time application.*

Keywords

Disease Classification, Local Pattern, Tomato Plant Diseases.

1. Introduction.

Tomato is one of the most common consumable products in the world. On time disease prediction in this plant is utmost important to meet the production requirements [1]. With the aid of technology, farmers can be assisted with a software solution to classify plant diseases. Image processing provides a direction to extract features from the plant leaves and classify them using the machine learning models automatically. Features are extracted either by hand-crafted methods or deep learning models. Over these features, classification is performed using machine learning classifiers. These systems are evaluated on the benchmarked plant leaves datasets. This solution is quick, hassle-free and accurate with less of human intervention. However, it is still critical to classify them because of several factors such as, brightness variation, shadowing, background, occlusion [2]. Therefore, it is important to classify images accurately irrespective of these challenges.

Many ensemble techniques alongwith their accuracies are summarised in [3]. Basavaiah et al. [4] has resized images and used histogram, Hu moments, Haralick and local binary pattern (LBP) features for the classification using random forest and decision tree models. Gray level co-occcurence matrix (GLCM), LBP, Gabor filters and scale invariant feature transform are used over PlantVillage dataset by Kaur et al. [5]. In [6], deep features are extracted using VGG-16 and classification is performed using kNN classifier. After image resizing and filtering histogram equalisation is done to improve the image contrast. A lot of research works are reviewed in [7]. Further, GLCM and LBP features are fed for support vector machine (SVM) in [8], for classification. Pham et al. [9] has compared AlexNet, VGG16, ResNet-50 with feed-forward neural network for mango leaves classification. Different types of features such as, color, texture, geometrical features are extracted and the best features are selected in [10]. Many deep learning networks are evaluated in [11], over six plant diseases, namely, tomato, potato, rice, corn, grape, and apple. A new model, dense inception convolutional neural network is designed by Liu et al. [12] for grapes diseases classification. U-net and Modified U-net are used for two, six and ten class problem in [13].

Similar to LBP, features can also be computed using local ternary pattern (LTP) and their co-occurrence (LTCoP). Interleaving of Gaussian filtered image with the original image is used to compute Gaussian local ternary co-occurrence pattern (GLTCoP) [14]. In [15], a 3D structure is designed by arranging five Gaussian images and LTCoP is computed. Both color and texture capture significant details to identify images, hence, they are also used together in literature. Multiple color channels are explored together to design multichannel local ternary pattern (MCLTP) [16]. Co-occurrence of MCLTP is computed in MCLTCoP [17]. First and second order derivative responses are interleaved in [18], for directional information extraction. Two neighborhoods with radius 1 and 2, are used in Haar-like local ternary co-occurrence pattern (HLTCoP) [19].

In literature, various feature extraction methodologies are proposed. Some of them are extracting global features over the image while, some are computing patterns locally. These features overlook the frequency content present in the image, and hence, significant information gets neglected. Also, few deep learning networks are being used in the literature for the classification. But, deep networks require large dataset for training as well as system computational requirement is high.

The main aim of the current study is to firstly, propose a hand-crafted feature extraction method after decomposing the image into different frequency sub-bands and perform classification using machine learning classifier. Secondly, compute features using deep networks also to compare with the bench marks.

In this paper, frequency decomposed local ternary pattern (FDLTP) is proposed. Different sub-bands are extracted through the images to visualize detailed information. Local information is analyzed by using LTP patterns. Histograms of hue and saturation planes along-with gray images are concatenated for global outlook. Major highlights of the proposed system are as follows:

- Four frequency sub-bands are used to capture variations at different frequency levels.
- Local neighborhood block is used to analyze texture statistics of pixels.
- Ternary patterns are used to compute LTP histograms.
- Global information is added through HSV color space. This makes it a more comprehensive feature.

These properties of proposed feature help to capture fine to coarse information and detect diseased leaves efficiently. Performance of various machine learning classifiers is compared. On the popular Taiwan tomato leaves dataset, proposed feature has performed better than deep learning models as well.

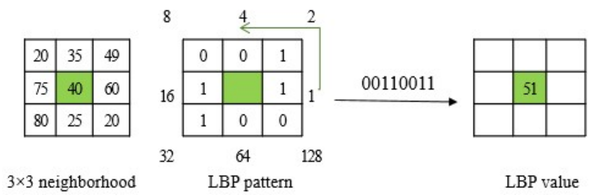

Fig. 1: LBP computational steps.

Rest of the paper is organised as follows: Section 2. gives basics of local pattern computation, Section 3. discusses about proposed system framework along with classifiers and performance evaluation measures. Section 4. illustrates experimental details on Taiwan dataset and in Section 5. conclusion is summarised.

2. Background

Local patterns are the simple features to analyse images. Local binary pattern (LBP) is most popular local feature proposed by Ojala et at. [20]. A 3×3 neighborhood of radius $r = 1$ is selected to compare pixels in all the directions with reference to the center pixel. Computation of LBP is as follows:

$$LBP_n^r = \begin{bmatrix} 1 & I_n^r > I_c \\ 0 & I_n^r \leqslant I_c \end{bmatrix}. \quad (1)$$

Center pixel I_c is compared with I_n^r where $1 \leqslant n \leqslant 8$ is denoting neighboring pixels. Computaional steps of LBP are shown in Fig. 1. Arrow points the movement of pixel comparison considered as LSB to MSB in anticlock-wise direction. Corresponding decimal weightage is written adjacent to the cell. LBP values are obtained from these 8 bit LBP patterns as follows:

$$LBP_v = \sum_{n=1}^{8} 2^{n-1} \times LBP_n^1. \quad (2)$$

These values are converted into hisotgrams of 0-255 bins.

3. Proposed System Framework

The outlook of the proposed classification model is shown in Fig. 2. There are four sequential major steps. In the first step, the Taiwan tomato leaves dataset is

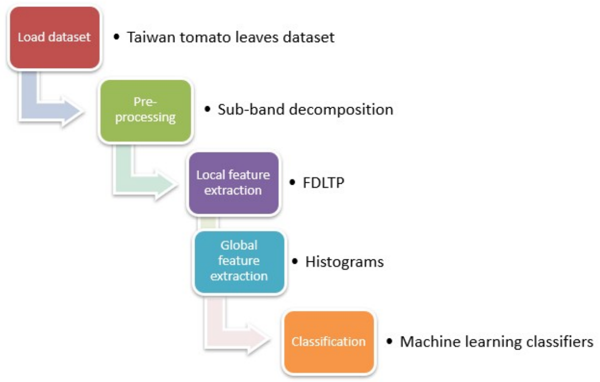

Fig. 2: Proposed retrieval system framework.

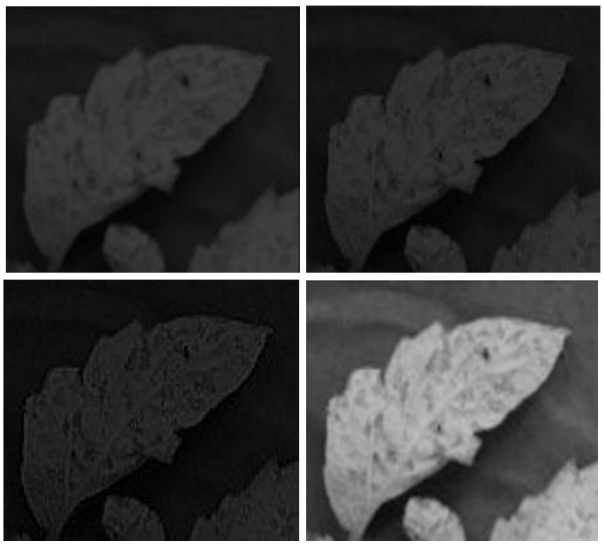

Fig. 3: Sub-band images generated by F_1, F_2, F_3 and F_4 filters (row wise).

loaded. In the second step, all the images are decomposed into sub-bands using Gaussian filters. Thereafter, local feature, frequency band local ternary pattern (FDLTP) is extracted to analyse texture statistics of leaf images using ternary patterns. Broader features are extracted using histograms of color images. At the end, both types of features are given as input to the machine learning classifier. It detects unhealthy/diseased and healthy leaves quickly based on the extracted features. Performance using four machine learning classifiers, support vector machine (SVM), k-nearest neighbour (kNN), decision tree (DT) and bagged tree is compared. Details of feature extraction and classifiers is given in the following subsections.

3.1. Feature Computation

In this work, we have compared both, hand-crafted as well as deep learning features for classification purpose. Proposed hand-crafted features are classified using various machine learning models. Deep learning feature

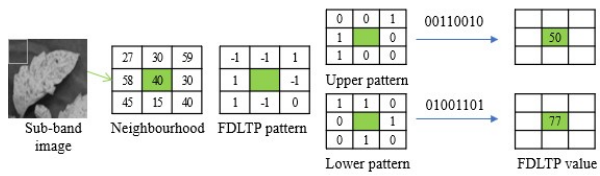

Fig. 4: FDLTP computation.

are classified using multi-class SVM classifier. In the following subsections details of both the approaches are given. Using hand-crafted method, image frequency information is segregated in the form of sub-bands for the local feature computation. It helps to capture the image content variations more precisely.

1) Proposed Hand-Crafted Features

In this paper, FDLTP is proposed. All the colored images are converted into gray-scale. Four Gaussian filters, $F_i(m,n)$ are designed for image sub-bands decomposition as follows:

$$F_1(m,n) = \delta(m,n) - \frac{1}{2\Pi\sigma_1^2} e^{\frac{-\left(m^2+n^2\right)}{2\sigma_1^2}}, \tag{3}$$

$$F_2(m,n) = \frac{1}{2\Pi}\left[\frac{1}{\sigma_2^2} e^{\frac{-\left(m^2+n^2\right)}{2\sigma_2^2}} - \frac{1}{\sigma_1^2} e^{\frac{-\left(m^2+n^2\right)}{2\sigma_1^2}}\right], \tag{4}$$

$$F_3(m,n) = \frac{1}{2\Pi}\left[\frac{1}{\sigma_3^2} e^{\frac{-\left(m^2+n^2\right)}{2\sigma_3^2}} - \frac{1}{\sigma_2^2} e^{\frac{-\left(m^2+n^2\right)}{2\sigma_2^2}}\right], \tag{5}$$

$$F_4(m,n) = \frac{1}{2\Pi\sigma_3^2} e^{\frac{-\left(m^2+n^2\right)}{2\sigma_3^2}}. \tag{6}$$

where δ represents delta function and σ_1, σ_2, and σ_3 are 0.4, 0.5 and 0.6, respectively. Thereafter, response images are computed by convolving these filters with the image, I as follows:

$$FI_i(m,n) = I \otimes F_i(m,n). \tag{7}$$

On each of the sub-band image as generated above, local features are computed. Fig. 3 shows response images corresponding to all the four sub-bands. Local neighborhood of 3×3 size and radius, $r = 1$ is used to extract texture features. Intensity differences in the local neighbourhood are computed by comparing center pixel value with the neighboring eight pixels. Sign of difference is encoded into ternary patterns by using following equation.

$$FDLTP_i^n = \begin{bmatrix} 1 & FI_i^n > FI_i^c \\ 0 & FI_i^n = FI_i^c \\ -1 & FI_i^n < FI_i^c \end{bmatrix}, \tag{8}$$

where FI_i^c represents center pixel of the i^{th} filtered image and FI_i^n represents n^{th} surrounding pixel of i^{th}

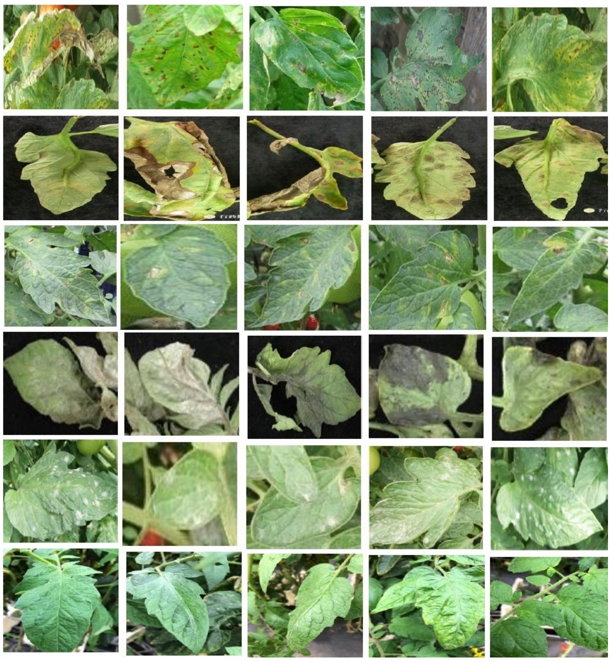

Fig. 5: Images from Taiwan tomato leaves database (Top to down rows): bacterial spot, black leaf mold, gray leaf spot, late blight, powdery mildew and healthy category.

filtered image. Surrounding pixel is assigned as upper pattern '1', if it has larger value than center pixel. Surrounding pixel is assigned as lower pattern '-1', if it has smaller value than center pixel. Equal values are turned into '0' pattern. 8-bit patterns generated in such a manner are transformed into upper and lower pattern values ranging from 0-255. Finally, their upper and lower histograms are created to give the FDLTP feature. Fig. 4 illustrates the computation of FDLTP features for an example neighborhood.

The global outlook of the image is captured by histograms of gray scale image, hue and saturation channels. Color and gray features are appended together to get the final hand-crafted feature.

2) Deep Learning Features

In this work, three deep learning models VGG16, AlexNet and GoogleNet are used for feature extraction. VGG16 was proposed in Visual Geometry Group Lab of Oxford University in 2015 [21]. It is a deep convolutional neural network (CNN) model trained on ImageNet subset. It has 13 convolutional layers, 5 max pooling layers, 3 dense layers and 16 layers with learnable parameters. Features are taken through pool5 layer.

AlexNet has 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer [22]. Each convolutional layer has convolutional filter followed by nonlinear activa-

Fig. 6: Confusion matrix of DT classifier.

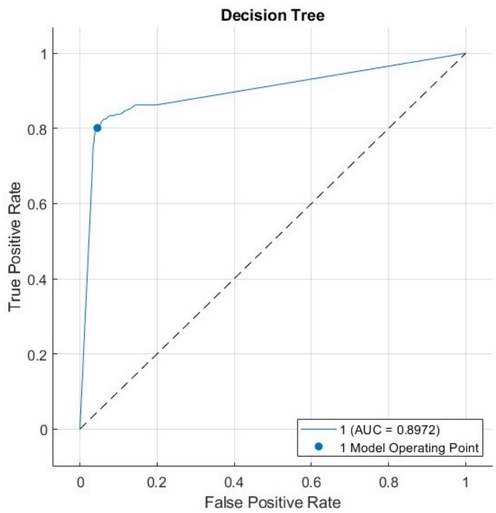

Fig. 7: ROC of DT classifier.

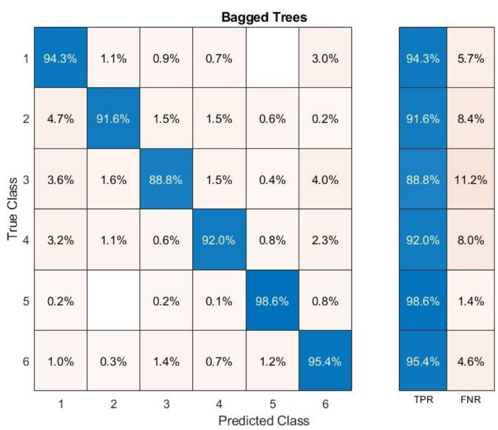

Fig. 8: Confusion matrix of BT classifier.

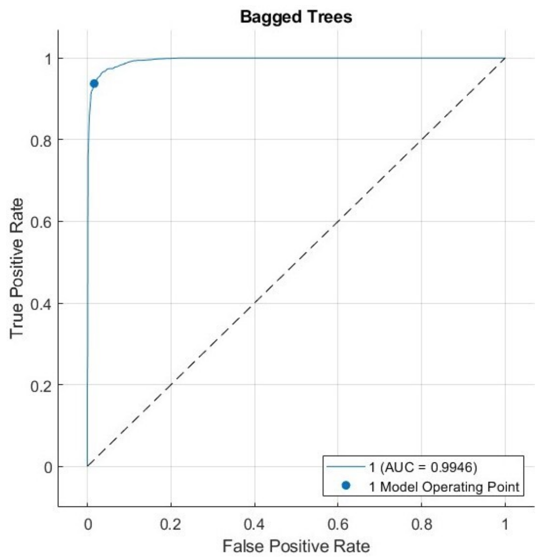

Fig. 9: ROC of BT classifier.

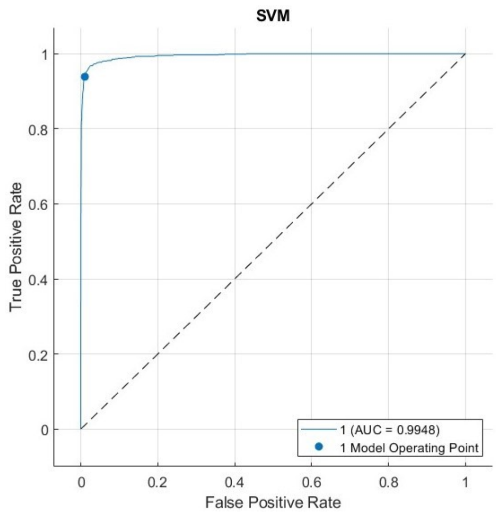

Fig. 11: ROC of SVM classifier.

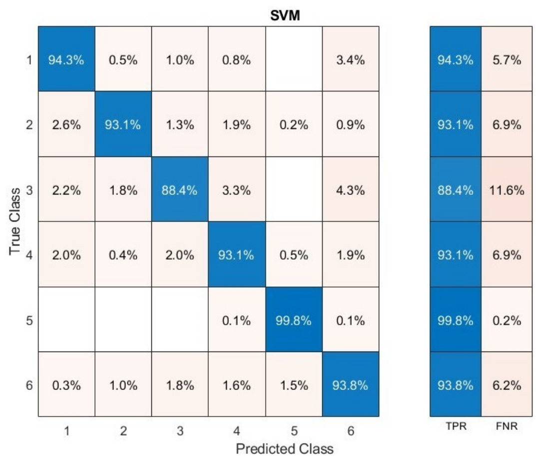

Fig. 10: Confusion matrix of SVM classifier.

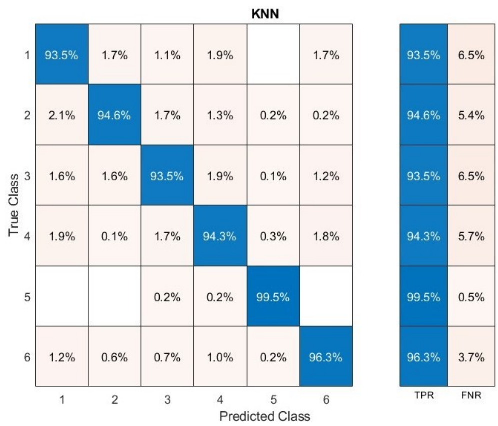

Fig. 12: Confusion matrix of kNN classifier.

tion function ReLU. Features are taken through pool5 layer.

GoogleNet is also called Inception V1 and it was proposed by research at Google in 2014 [23]. It is 22 layers deep architecture. Inception module was introduced in GoogleNet for deep learning. Features are taken through pool5-7 $\times$ 7_S1 layer.

3.2. Machine Learning Classifiers

A brief of the four different classifiers used in the performance evaluation is given in the following subsection. All the hyper-parameters are tuned automatically using MATLAB in-built functions classification results are validated using 10-fold cross validation.

1) Decision Tree (DT)

It provides a supervised graphical representation in terms of tree-like structure which includes leaf nodes as the output nodes and decision nodes as the internal nodes [24]. Features are stored in the internal nodes and are used to make simple yes/no decision by selecting the appropriate feature branch and progress towards the leaf node. This structure is easy to understand.

2) Bagged Tree (BT)

It is an ensemble method to combine many DTs and has advantages of different models together [25]. It minimizes variance and keeps bias consistent. Bootstrap samples of the training data are used to create trees and their outputs are aggregating to predict the final output.

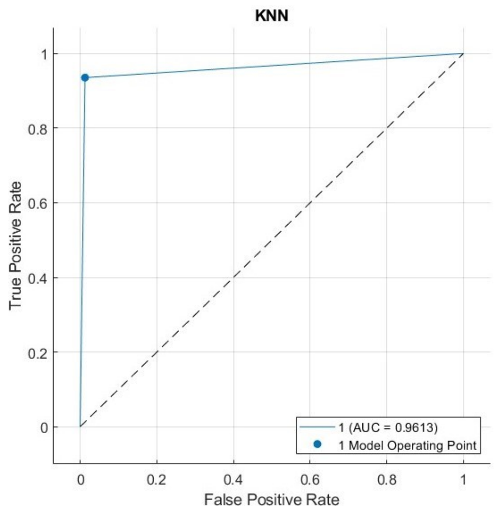

Fig. 13: ROC of kNN classifier.

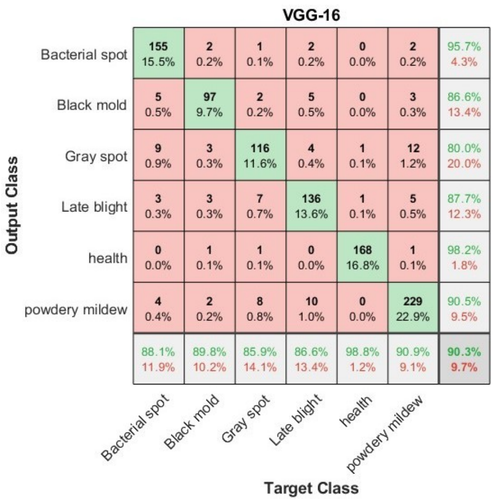

Fig. 14: Confusion matrix of VGG-16 model.

3) Support Vector Machine (SVM)

SVM creates hyperplanes to separate different classes [26]. Hyperplanes are selected such as to maximizes their margin and also their distance to the nearest feature points. Linear and non-linear kernels are used depending upon the dataset to be classified. In the case of non-linear dataset, firstly the data is mapped to a higher dimension to draw the hyperplane and then brought back to the lower dimension. In this work, cubic kernel is used.

4) k-nearest Neighbour (kNN)

kNN selects the k nearest neighbours of a test feature point and saves their class labels [27]. Label assigned to the most of the k nearest neighbors becomes the class of the test data point. User can change the value of the k and distance metric used for comparing features. In this work, city-block distance is used.

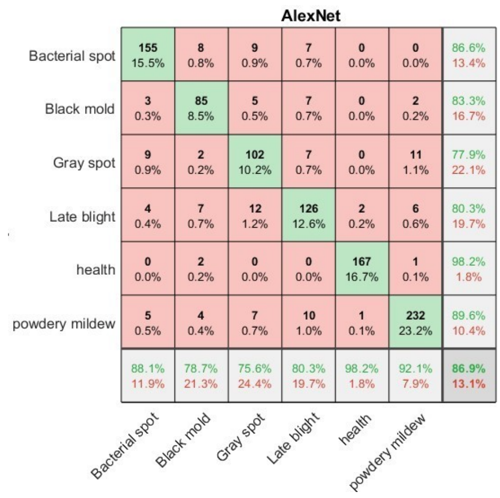

Fig. 15: Confusion matrix of AlexNet model.

3.3. Performance Evaluation

On the Taiwan tomato dataset, experiment is performed on a system using MATLAB 2017a with Intel Core i5 processor, 8GB RAM and 500GB hard drive. Classification performance is evaluated using various parameters, such as, accuracy, area under curve (AUC), true positive rate (TPR), and false negative rate (FNR). Accuracy is most popular criteria to verify the performance of any system. It represents the percentage of correctly classified samples out of total samples. In the current dataset, we have 4976 images so, total samples will be 4976. To analyse the class wise performance, TPR and FNR are computed. TPR is also called as sensitivity, it represents the proportion of correct prediction of positive class. FNR is the incorrect prediction of negative class. In other words, it represents prediction of negative class as positive class. Region under curve (ROC) plots the TPR versus FPR for different thresholds of classification scores. AUC represents integral of a ROC curve, TPR with respect to FPR. AUC values are between 0-1. Higher the value of AUC better will be the classifier performance.

Tab. 1: Taiwan tomato leaves database summary.

Class #	Class name	# Images
1	Bacterial Spot	880
2	Black mold	536
3	Gray spot	672
4	Health	848
5	Late blight	784
6	Powdery mildew	1256

4. Experiments

Performance of the proposed system is evaluated on the benchmarked Taiwan tomato leaves dataset [28]. This dataset is publicly available. In Table 1 summary of the dataset is given with number of images

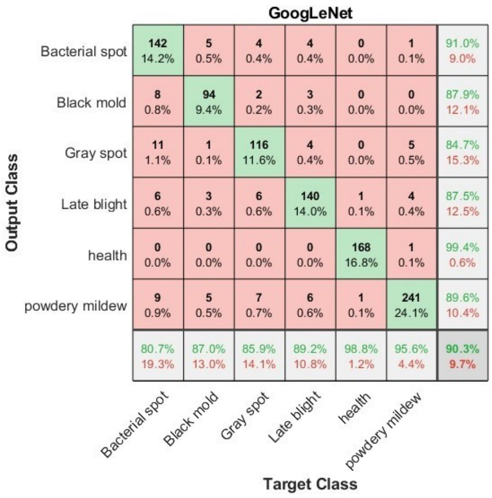

Fig. 16: Confusion matrix of GoogLeNet model.

in each class after augmentation. These classes are labelled from 1 to 6 in top to down order, in further results. This dataset is published by Huang and Chang in 2020. It has a total of five different diseased categories, bacterial spot, black leaf mold, gray leaf spot, late blight, powdery mildew and one healthy category. Sample images from each category are shown in Fig. 5. These images have single or multiple leaves and plain or complex background. Originally there were 622 images, after data augmentation number of images are increased to 4976. For this process, images are rotated clockwise with 90^o, 180^o and 270^o angles, horizontally mirrored, vertically mirrored, brightness increased, and brightness decreased. Images are of 227×227 sizes and JPG format.

After feature extraction, machine learning classifiers are used for classification. Fig. 6 and Fig. 7 show confusion matrix and ROC using DT classifier. In Fig. 6, x-axis and y-axis show predicted and true classes, respectively. Last two column show TPR and FNR. AUC value is 0.89 for class 1 using DT. Similarly, Fig. 8, Fig. 9, Fig. 10, Fig. 11, Fig. 12 and Fig. 13, show confusion matrix and ROC using BT, SVM and kNN, respectively. Their AUC values are 0.99, 0.99 and 0.96, respectively for class 1. Accuracy values are summarised in Table 2. It is observed that accuracy of the proposed method is 95.6%, for kNN classifiers and it is better than to DT, BT and SVM.

Tab. 2: Comparison with deep learning models.

Classifiers	Accuracy (%)
DT	79.8
BT	93.9
SVM	94
kNN	**95.6**

Further, features are also extracted using deep learning pre-trained models, VGG16, GoogleNet and AlexNet namely, and classification is performed using multi-class SVM. Fig. 14, Fig. 15 and Fig. 16 show confusion matrix for each of them, respectively. The results are summarized in Table 3. It is observed that as compared to the deep learning models proposed method is giving better accuracy. Apart from this deep learning models need more computational time and memory as compared to the hand-crafted features.

Tab. 3: Comparison with deep learning models.

Methods	Accuracy (%)
VGG-16	90.28
GoogLeNet	90.28
AlexNet	86.87
Proposed method	**95.6**

5. Conclusion

In this paper, a new feature FDLTP is proposed to identify the diseased crop of tomotos. In contrast to other pattern features, FDLTP decomposes the image into 4 frequency sub-bands using Gaussian filters. It helps to analysis the individual sub-band statistics in a better manner. All these sub-bands are fed for local feature extraction. LTP is computed in the small neighborhood by comparing the intensity differences. Small variations occured due to defect is captured and utilized to differentiate diseased samples with the healthy samples. Results are also compared with the existing pre-trained deep learning models. On the banchmarked dataset better results are obtained by the proposed hand-carfted features. It is first of its kind method for crop diesese classification. In future, similar features may be designed for other crop disease identification.

Author Contributions

Megha Agarwal has conceptualized the idea, arranged the data, implemented methodology, validated results and written the manuscript.

References

[1] BATOOL, A., S. B. HYDER, A. RAHIM, N. WAHEED, M. A. ASGHAR, and FAWAD. 2020. Classification and Identification of Tomato Leaf Disease Using Deep Neural Network. In: *2020 International Conference on Engineering and Emerging Technologies. (ICEET). Lahore, Pakistan: IEEE*, 2020, pp. 1-6. ISSN 2409-2983. DOI: 10.1109/ICEET48479.2020.9048207.

[2] BARBEDO, J. G. A. Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. *Computer and. Electronics in Agricul-*

ture. 2018, vol. 153, pp. 46–53. ISSN 1872-7107. DOI: 10.1016/j.compag.2018.08.013.

[3] ASTANI, M., M. HASHEMINEJAD, M. VAGHEFI. A diverse ensemble classifier for tomato disease recognition. *Computers and Electronics in Agriculture*. 2022, vol. 198, pp. 107054, ISSN 0168-1699. DOI: 10.1016/j.compag.2022.107054.

[4] BASAVAIAH, J., A. A. ANTHONY. Tomato leaf disease classification using multiple feature extraction techniques. *Wireless Personal Communications*. 2020, vol. 115, iss. 1, pp. 633–651. ISSN 1572-834X. DOI: 10.1007/s11277-020-07590-x.

[5] KAUR, N., V. DEVENDRAN. Plant leaf disease detection using ensemble classification and feature extraction. *Turkish Journal of Computer and Mathematics Education*. 2021, vol. 12, iss. 11, pp. 2339–23352. ISSN 1309-4653.

[6] ZHANG, Y., C. SONG, D. ZHANG. Deep learning-based object detection improvement for tomato disease. *IEEE Access*. 2020, vol. 8, pp. 56607–56614. DOI: 10.1109/ACCESS.2020.2982456.

[7] SUPIAN, M. B. A., H. MADZIN, E. ALBAHARI. Plant Disease Detection and Classification Using Image Processing Techniques: A review. In: *2019 2nd International Conference on Applied Engineering (ICAE), Batam, Indonesia*. 2019, pp. 1-4. ISBN:978-1-7281-2807-8. DOI: 10.1109/ICAE47758.2019.9221712.

[8] OO, Y. M., N. C. HTUN. Plant leaf disease detection and classification using image processing. *International Journal of Research and Engineering*. 2018, vol. 5, iss. 9, pp. 516–523. DOI: 10.21276/IJRE.2018.5.9.4.

[9] PHAM, T. N., L.V. TRAN, S. V. T. DAO. Early disease classification of mango leaves using feed-forward neural network and hybrid metaheuristic feature selection. *IEEE Access*. 2020, vol. 8, pp. 189960-189973. DOI: 10.1109/ACCESS.2020.3031914.

[10] SHARIF, M., M. A. KHAN, Z. IQBAL, M. F AZAM, M. I. U LALI, M. Y. JAVED. Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. *Computer and. Electronics in Agriculture*. 2018, vol. 150, pp. 220–234. DOI: 10.1016/j.compag.2018.04.023.

[11] KABIR, M. M., A. Q. OHI, M. F. MRIDHA. A Multi-Plant Disease Diagnosis Method Using Convolutional Neural Network. In: *Computer Vision and Machine Learning in Agriculture*. 2021, pp. 99–111. ISSN 2524-7573. DOI: 10.1007/978-981-33-6424-0_7.

[12] LIU, B., Z. DING, L. TIAN, D. HE, S. LI, H. WANG. Grape leaf disease identification using improved deep convolutional neural networks. *Frontiers in Plant Sciences*. 2020, vol. 11, pp. 1-14. DOI: 10.3389/fpls.2020.01082

[13] CHOWDHURY, M. E. H., T. RAHMAN, A. KHANDAKAR, M. A. AYARI, A. U. KHAN, M. S. KHAN, N. AL-EMADI, M. B. I. REAZ, M. T. ISLAM, S. H. M. ALI. Automatic and reliable leaf disease detection using deep learning techniques. *Agri Engineering*. 2021, vol. 3, iss. 2, pp. 294–312. ISSN: 2624-7402. DOI: 10.3390/agriengineering3020020.

[14] SINGHAL, A., M. AGARWAL. Gaussian Local Ternary Co-occurrence Pattern for Image Retrieval. In: Saran, V.H., Misra, R.K. (eds) Advances in Systems Engineering. Lecture Notes in Mechanical Engineering. *Springer, Singapore*. 2021, pp. 3-9. ISBN 978-981-15-8027-7. DOI: 10.1007/978-981-15-8025-3_1.

[15] AGARWAL M., A. SINGHAL, B. LALL. 3D local ternary co-occurrence patterns for natural, texture, face and bio medical image retrieval. *Neurocomputing*. 2018, vol. 313, pp.333–345. ISSN 0925-2312. DOI: 10.1016/j.neucom.2018.06.027.

[16] AGARWAL M., A. SINGHAL. Multi-channel local ternary pattern for content-based image retrieval. *Pattern Analysis and Applications*. 2019, vol. 22, iss. 4, pp. 1585–1596. ISSN 1433-7541. DOI: 10.1007/s10044-019-00787-2.

[17] AGARWAL, M., R. P. MAHESHWARI. Multichannel Local Ternary Co-occurrence Pattern for Content-Based Image Retrieval. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*. 2020, vol. 44, pp. 495–504. ISSN 2228-6179. DOI: 10.1007/s40998-019-00219-1.

[18] SINGHAL, A., M. AGARWAL, R. B. PACHORI. Directional local ternary co-occurrence pattern for natural image retrieval. *Multimedia Tools and Applications*. 2021, vol. 80, pp. 15901–15920. ISSN 1380-7501. DOI: 10.1007/s11042-020-10319-4.

[19] AGARWAL, M., A. SINGHAL. Directional local co-occurrence patterns based on Haar-like filters. *Multimedia Tools and Applications*. 2022, vol. 81, pp. 1109–1123. ISSN 1380-7501. DOI: 10.1007/s11042-021-11361-6.

[20] OJALA, T., M. PIETIKAINEN, D. HARWOOD. A comparative study of texture measures with classification based on feature distributions. *Pat-*

tern Recognition. 1996, vol. 29, pp. 51–59. ISSN 0031-3203. DOI: 10.1016/0031-3203(95)00067-4.

[21] SIMONYAN, K., A. Zisserman. Very deep convolutional networks for large-scale image recognition. *III International Conference on Learning Representations. San Diego, USA*. 2015, pp. 1409–1556. DOI: https://doi.org/10.48550/arXiv.1409.1556.

[22] KRIZHEVSKY, A., I. SUTSKEVER, G. E. HINTON. ImageNet classification with deep convolutional neural networks. *Communications of the ACM*. 2017, vol. 60, iss. 6, pp. 84–90. ISSN 0001-0782. DOI: 10.1145/3065386.

[23] SZEGEDY, C., W. LIU, Y. JIA, P. SERMANET, S. REED, D. ANGUELOV, D. ERHAN, V. VANHOUCKE, R. ANDREW. Going deeper with convolutions. In: *IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Boston, MA. USA*. 2015, pp. 1-9. DOI: 10.1109/CVPR.2015.7298594.

[24] PODGORELEC, V., P. KOKOL, B. STIGLIC, I. ROZMAN. Decision trees: An overview and their use in medicine. *Journal of Medical Systems*. 2002, vol. 26, pp. 445–463. ISSN 1573-689X. DOI: 10.1023/a:1016409317640.

[25] JAVED A. A., R. A. POPA, R. L. RIVEST. On estimating the size and confidence of a statistical audit. In: *Proceedings of the USENIX Workshop on Accurate Electronic Voting Technology*. 2007, pp. 8.

[26] CORTES, C., V. VAPNIK. Support-vector networks. *Machine Learning*. 1995, vol. 20, iss. 3, pp. 273–297. ISSN 1573-0565. DOI: 10.1007/BF00994018.

[27] FIX, E., J. L. HODGES. Discriminatory Analysis. Nonparametric Discrimination: Consistency Properties. *International Statistical Review*. 1989, vol. 57, iss. 3, pp. 238-247. ISSN 1751-5823. DOI: 10.2307/1403797.

[28] Mendeley Dataset of Tomato Leaves 2020. Available at: 10.17632/ngdgg79rzb.1

About Authors

Megha AGARWAL (corresponding author) is working as Associate Professor at the Department of Electronics and Communication Engineering, Jaypee Institute of Information Technology, Noida. She received her M.Tech and Ph.D. degrees from Indian Institute of Technology, Roorkee, India. She obtained her B.Tech. degree in Electronics and Instrumentation Engineering from Rohilkhand University, Bareilly, India. Her research interests include image processing, biomedical signal/image processing and computer vision.