Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Leaf Disease Recognition using Ensemble of Laws' Masks Filters

Fauziah Kasmin[1,*], Sharifah Sakinah Syed Ahmad[1], Zuraini Othman[1], Nur Hajar Zamah Shari[2], Samarjeet Borah[3]

[1] Faculty of Information and Communication Technology, Universiti Teknologi Malaysia Melaka,76100, Durian Tunggal, Melaka Malaysia
[2] Forestry and Environment Division, Forest Research Institute Malaysia, Kepong, Malaysia
[3] Department of Computer Applications, SMIT, Sikkim Manipal University, India

ARTICLE INFO

Article history:
Received 26 February 2025
Received in revised form 26 July 2025
Accepted 14 August 2025
Available online 1 November 2025

Keywords:
Leaf disease recognition; Law's masks filter; histogram of oriented gradient; posterior probability

ABSTRACT

Despite a sharp rise in population, agriculture nevertheless provides food for all people. The control of plant diseases is essential for the preservation of the agroecosystem and the safeguarding of food. To recognise plant diseases, computer-aided methods using artificial intelligence are required. Many techniques previously have been discussed on how to recognise plant disease effectively. One of the methods that are popular to increase the accuracy of the recognition is by using an ensemble approach. Histograms of oriented gradient (HOG) have been used widely as features in detecting disease from leaves. However, HOG is susceptible to rotation and hence makes the recognition accuracy low. In order to overcome the problem, Laws' mask filters have been applied towards the images of leaves that have been affected by disease. For each Law's mask filter, HOG features are extracted from the leaf and classified by classifier support vector machine (SVM). For each Laws' mask filter, posterior probability gained from SVM is given weight and then added for a particular class. The highest probability obtained from this method is a chosen class for a particular image. The method is applied to 4062 images of grape leaves that contain several types of diseases and healthy leaves. The accuracy of recognition is encouraging, and it serves as a solid indication that the ensemble of Laws' mask filters can aid in enhancing recognition performance.

1. Introduction

Plants are vital for the balance of nature and they are important in people's lives. Furthermore, plants provide food and energy for all living beings who cannot synthesize food. Not only food, there are many products from plants that are vital to human such as oils, wood, latex and many more. Besides that, petroleum and coal originate from fossil substance which include also plants. Thus, plant provide many form of products such as fuels, medicines, clothing, shelter and many more. Since plant are very useful to human, then it is very important to protect plant from any diseases. However, major threat of food security is crop diseases [1-3]. The management of plant diseases is very crucial for food protection and agro-ecosystem sustainability [2,4,5].

* *Corresponding author.*
E-mail address: fauziah@utem.edu.my

https://doi.org/10.37934/ard.146.1.233243

There are many successful results from researchers who have applied image processing techniques in detecting the plant diseases [6-10]. Omrani *et al*., [6] have used colour, gray-level occurrence matrix and wavelet features to describe each image. Then, they compare between support vector regression (SVR) that used radial basis function (RBF) kernel, support vector regression that used polynomial kernel and artificial neural network. From their experiment, they have found SVR that used radial basis function gave the best results. Another approach that have been considered in detecting plant diseases is deep learning approach. There are many researchers who have used deep learning approach in identifying plant disease such as in Mohanty *et al*., [1], Ferentinos [7] and Zhang *et al*., [11]. Mohanty *et. al*., [1] have used different types of images that includes color, grayscale and segmented images. To identify plant diseases, researchers have employed deep learning techniques. They have compared between two architectures i.e. AlexNet and GoogLeNet. From the experiments, they have found that the performance of GoogLeNet is better compared to AlexNet. They also have found that colored version of images achieve the best performance compared to the other two types. However, their main limitation is the dataset used are images in laboratory setups and not in real condition. Ferentinos [7] have developed deep learning models where specific convolutional neural network have been trained and assessed plant disease recognition. He has used 2 types of datasets i.e. experimental and images in real field. They were comparing performance between five architectures in deep learning that are AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat and VGG. The results give good performances, and they suggest their approach can be as an early indicator in monitoring purposes. Research done by [9] using convolutional neural network for recognition of corn diseases. By altering hyper-parameters and combining them on a system, deep neural networks perform better.

Features are important as they provide distinctive properties that aid in discrimination of classes. Features retrieved from the leaf images of crop disease are generally sensitive to the illumination, orientation, and scale of the images [12,13] and one type of feature that are normally used in plant disease recognition is histogram of oriented gradients (HOG). HOG [14] had been extensively used in detecting object or person in a particular environment. There are many research have used HOG in recognition of plant or plant diseases [15-17]. However, HOG is very sensitive to image rotation [17]. Due to that, Laws' masks filters developed by Law [18] have been used to help HOG in improving the recognition of plant diseases. There are five types of masks in Laws' masks filters. They are Spot (S), Level (L), Wave (W), Edge (E) and R (Ripple) where rotational invariance can be achieved by getting the average of matched pairs of masks. By using advantages of HOG and Laws' masks filters, a leaf disease recognition is proposed. The main contribution of our method are: (1) an ensemble learning approach for leaf diseased recognition is proposed by integrating Laws' masks filters and HOG descriptors. (2) the effectiveness of the proposed approach is validated on a standard leaf disease recognition database.

The remaining sections of this paper are structured as follows. The procedures utilized in the experiments are described in Section 2. The experimental design is covered in Section 3, and the experiment's findings are shown in Section 4. The findings are discussed in Section 5, which also serves as the paper's conclusion.

2. Methodology

In this section, background study of the techniques used is presented.

2.1 HOG Descriptor

The purpose of HOG is as descriptors for object detection. There are several steps to follow [14, 18]:

a. Computation of gradient – magnitude of gradient and angle is computed by using these formulas.

$$\text{Gradient} = \sqrt{dy^2 + dx^2} \quad (1)$$

where gradient is the small change in x and y directions.

$$\text{Angle,} \quad \theta = \arctan\left(\frac{dy}{dx}\right) \quad (2)$$

b. Orientation binning.
The histogram's cell for descriptor block is calculated. 9 orientation bins are being used. This orientation bin is calculated for each orientation of the pixels.

c. Descriptor Blocks
The orientation histograms of the cells are transformed into blocks. The transformation is done so that the cells are normalized. The transformation process used R-HOG.

d. Block Normalization
Block normalization is done by using L2-Norm normalization technique.

$$f = \frac{v}{\sqrt{\|v\|_2^{\,2} + e^2}} \quad (3)$$

e. Detection Window
Each R-HOG block is made up of 2×2 cells, each of which is 8×8 pixels and has a 1×9 histogram vector.

2.2 Laws' Mask filter

Despite being quite popular in texture analysis, Laws' mask technique is not noise-resistant [6]. Kenneth Ivan Laws' proposed the Laws' masks method of feature extraction in 1980 [18], with the fundamental idea being to filter images with specified masks created from a collection of one-dimensional kernel vectors to assess texture qualities. The Laws mask filters have five different kinds of masks. They are called R (Ripple), Wave (W), Edge (E), Level (L), and Spot (S). To determine an image's textural properties, the Laws' masks compare the pixel neighborhood to a number of common masks [11]. Additionally, this image processing technique can be broken down into 5×5 and 3×3 dimensions. Three straightforward vectors of length 3,

$$L3\ (1, 2, 1),\ E3\ (1, 0, 1),\ \text{and}\ S3\ (1, 2, 1),$$

which known as texture energy measure. They are used to extract the one-dimensional techniques of center-weighted local averaging and symmetric first differencing (edge detection).

For a 1-dimensional vector, we can convolve these vectors with one another or themselves as follows to produce five 5-dimensional vectors.

$$L5 = L3 \times L3 = [\ 1\ 4\ 6\ 4\ 1] - \text{level}$$
$$E5 = L3 \times E3 = [-1\ -2\ 0\ 2\ 1] - \text{edge}$$
$$S5 = -E3 \times E3 = L3 \times S3 = [-1\ 0\ 2\ 0\ -1] - \text{spot}$$
$$R5 = S3 \times S3 = [1\ -4\ 6\ -4\ 1] - \text{ripple}$$
$$W5 = -E3 \times S3 = [-1\ 2\ 0\ -2\ 1] - \text{wave}$$

The 2D convolution mask is then calculated using the output of the vector pairs. For 2-dimensional vectors, sets of more vectors might take the following forms as in Table 1:

Table 1
25 2D 5 by 5 mask texture maps

	L5	**E5**	**S5**	**R5**	**W5**
L5	L5L5	L5E5	L5S5	L5 R5	L5 W5
E5	E5L5	E5E5	E5S5	E5 R5	E5 W5
S5	S5L5	S5E5	S5S5	S5 R5	S5 W5
R5	R5L5	R5E5	R5S5	R5R5	R5W5
W5	W5L5	W5E5	W5S5	W5R5	W5W5

From a one-dimensional Law's filter, 25 texture maps of a 2D 5×5 mask can be generated. There are fifteen maps produced once the symmetry pairs are connected. It can be seen in Table 2. For instance, the E5S5 texture energy map offers vertical wave content while the S5E5 texture energy map offers horizontal wave content. The mean of E5S5/S5E5 therefore represents the whole wave content, which includes both vertical and horizontal wave content. The notation in Table 2 will be used for explaining proposed method in Section 3.

Table 2
15 2D 5 by 5 mask texture maps

Notation	Texture Map	Notation	Texture Map
Law1	L5L5	Law9	R5L5/L5R5
Law2	E5E5	Law10	S5L5/L5S5
Law3	S5S5	Law11	W5E5/E5W5
Law4	R5R5	Law12	W5S5/S5W5
Law5	W5W5	Law13	R5E5/E5R5
Law6	E5L5/L5E5	Law14	R5S5/S5R5
Law7	W5L5/L5W5	Law15	W5R5/R5W5

3. Proposed Method

The experiment started with pre-processing. Pre- processing used in this work is applied from [1]. After pre-processing stage, filtering stage have been applied. The filtered images were then used to extract features. After that, a support vector machine (SVM) classifier is used to categorise the images. The whole process of this work is shown as in the block diagram in Figure 1.

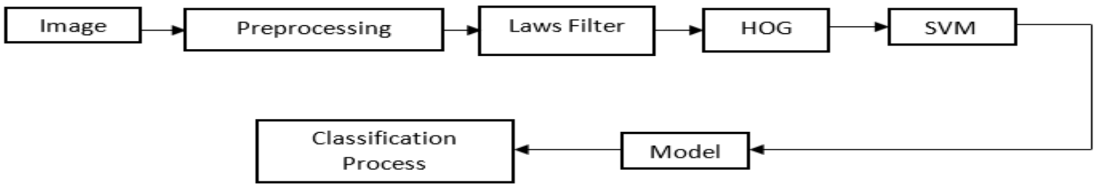

Fig. 1. Block Diagram of the proposed approach

Laws' filters have been applied towards the pre-processed images. There are 15 images have been obtained after applying Laws' filter. The Laws' filter applied are the same as in the Table 2. After applying Laws' filter, then HOG will be extracted from the corresponding filters. Support Vector Machine (SVM) is used to classify each image into 4 classes that are black rot, black measles, leaf blight and healthy leaves, respectively. For each class, probability for the classification to each class can be obtained. Based on these probabilities, weight will be applied to each classes for each Laws' filter. The weight applied for each Laws' filter is high when the probability is high while lower weight is applied for lower probability. Then this probability is added for each class and named as additive weighted probability of classes. The image that receive the highest probability for a particular class, will be classified as the respective class. The process of classification using additive weighted probability of classes have been simplified as in Figure 2. The notation used in Figure 2 are as follows:

*Pb*_1 is the notation for posterior probability for class 1
*Pb*_2 is the notation for posterior probability for class 2
*Pb*_3 is the notation for posterior probability for class 3
*Pb*_4 is the notation for posterior probability for class 4

These are the equations that have been used in the Additive Weighted Probability of classes algorithm for *Pb*_1, *Pb*_2, *Pb*_3 and *Pb*_4:

$$Pb\_1 = w_1 \text{ProbLaw1}_1 + w_2\text{ProbLaw2}_1 + w_3\text{ProbLaw3}_1 + w_4\text{ProbLaw4}_1 + w_5\text{ProbLaw5}_1 + w_6\text{ProbLaw6}_1 + w_7\text{ProbLaw7}_1 + w_8\text{ProbLaw8}_1 + w_9\text{ProbLaw9}_1 + w_{10}\text{ProbLaw10}_1 + w_{11}\text{ProbLaw11}_1 + w_{12}\text{ProbLaw12}_1 + w_{13}\text{ProbLaw13}_1 + w_{14}\text{ProbLaw14}_1 + w_{15}\text{ProbLaw15}_1 \quad (4)$$

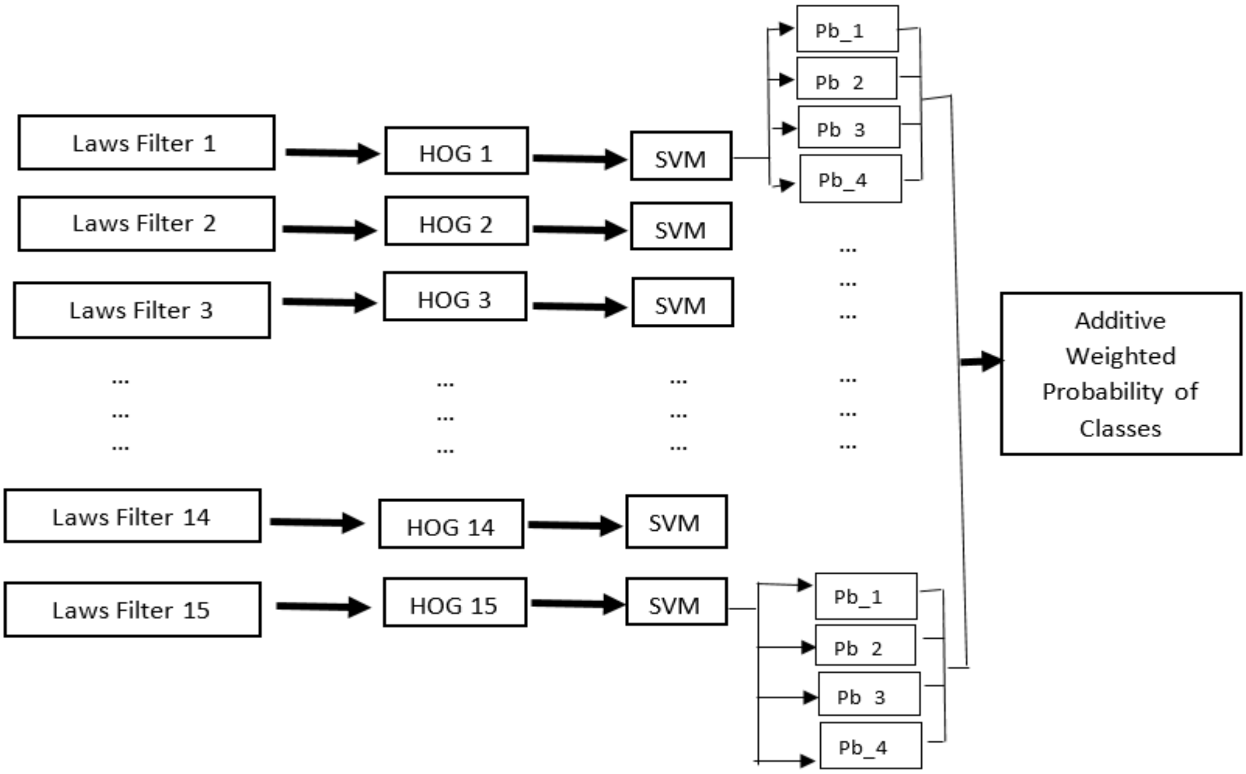

Fig. 2. Additive weighted probability of classes

$$Pb\_2 = w_1\,\mathrm{ProbLaw1}_2 + w_2\mathrm{ProbLaw2}_2 + w_3\mathrm{ProbLaw3}_2 + w_4\mathrm{ProbLaw4}_2 + w_5\mathrm{ProbLaw5}_2 + w_6\mathrm{ProbLaw6}_2 + w_7\mathrm{ProbLaw7}_2 + w_8\mathrm{ProbLaw8}_2 + w_9\mathrm{ProbLaw9}_2 + w_{10}\mathrm{ProbLaw10}_2 + w_{11}\mathrm{ProbLaw11}_2 + w_{12}\mathrm{ProbLaw12}_2 + w_{13}\mathrm{ProbLaw13}_2 + w_{14}\mathrm{ProbLaw14}_2 + w_{15}\mathrm{ProbLaw15}_2 \tag{5}$$

$$Pb\_3 = w_1\,\mathrm{ProbLaw1}_3 + w_2\mathrm{ProbLaw2}_3 + w_3\mathrm{ProbLaw3}_3 + w_4\mathrm{ProbLaw4}_3 + w_5\mathrm{ProbLaw5}_3 + w_6\mathrm{ProbLaw6}_3 + w_7\mathrm{ProbLaw7}_3 + w_8\mathrm{ProbLaw8}_3 + w_9\mathrm{ProbLaw9}_3 + w_{10}\mathrm{ProbLaw10}_3 + w_{11}\mathrm{ProbLaw11}_3 + w_{12}\mathrm{ProbLaw12}_3 + w_{13}\mathrm{ProbLaw13}_3 + w_{14}\mathrm{ProbLaw14}_3 + w_{15}\mathrm{ProbLaw15}_3 \tag{6}$$

$$Pb\_4 = w_1\,\mathrm{ProbLaw1}_4 + w_2\mathrm{ProbLaw2}_4 + w_3\mathrm{ProbLaw3}_4 + w_4\mathrm{ProbLaw4}_4 + w_5\mathrm{ProbLaw5}_4 + w_6\mathrm{ProbLaw6}_4 + w_7\mathrm{ProbLaw7}_4 + w_8\mathrm{ProbLaw8}_4 + w_9\mathrm{ProbLaw9}_4 + w_{10}\mathrm{ProbLaw10}_4 + w_{11}\mathrm{ProbLaw11}_4 + w_{12}\mathrm{ProbLaw12}_4 + w_{13}\mathrm{ProbLaw13}_4 + w_{14}\mathrm{ProbLaw14}_4 + w_{15}\mathrm{ProbLaw15}_4 \tag{7}$$

where ProbLaw1, ProbLaw2 and the rest are referring to posterior class probability, Pr $(y = 1|x)$ from classification of SVM. Sigmoid function in equation (8) is used to calculate these probabilities.

$$\Pr(y = 1|x) \approx P_{A,B}(f) \equiv 1/(1 + \exp(Af + B)), \tag{8}$$

where $f = f(x)$ and A and B are the best parameter settings. This parameters have been derived from training set of (f_i, y_i) by using maximum likelihood estimation.

In order to select which class is the best for a particular image, the following rule is applied to a particular image.

$$\max(Pb\_1, Pb\_2, Pb\_3, Pb\_4) \tag{9}$$

The highest probability from (9), is selected as a class for a particular image.

4. Result and Discussion

In this work, sample images taken from Mishra [19], is used and it is decided to use only 3 types of diseases and 1 healthy type for grape leaf that include black rot, black measles and leaf blight. Figure 3 shows the sample of diseases of leaf and healthy leaf.

Black Rot

Black Measles

Leaf Blight

Healthy

Fig. 3. Type of diseases for grape leaf

There are about 4062 images of grape leaf that consist of 1180 for black rot disease, 1383 for black measles, 1076 for leaf blight and 423 for healthy grape leaf. Class 1 is for black rot, Class 2 is for black measles, Class 3 is for leaf blight and Class 4 is for healthy leaf.

The experiments have been repeated 10 times and each run will select different images. Performance measures that have been employed to assess the leaf recognition, is [20, 21]:

$$Accuracy = (TP + TN)/(TP + FP + TN + FN) \tag{10}$$

where TP – true positive, TN – true negative, FP – false positive and FN – false negative. The result of the recognition of grape leaf diseases are as in Table 3 and Table 4. For the results Without Using

Laws' Masks Filters are referring to the process of not applying any filter to the image. The HOG features have been extracted directly from the pre-processed image.

In Table 3, it can be seen that most Laws' masks filters giving the accuracy of recognition quite low with highest accuracy is 0.8688 from E5E5. The lowest recognition accuracy is 0.3958 and come from W5S5. Hence, it can conclude that, Laws' masks filters alone do not give high accuracy of recognition since when do not applying any Laws' masks filters, the accuracy is 0.8636 which is not really far from the best accuracy for Laws' masks filters. This is due to the Laws' masks filters do not robust to noise [18]. But, when refer to Table 4, the results are quite promising when the Laws' masks filter are combined. Additive Probability is the method that just add the posterior probability without considering the weight given to any Laws' mask filter. For this method, the accuracy of the recognition is increasing to 0.9003. It means that the ensemble of posterior probabilities for Laws' masks filters do help to increase the recognition accuracy. From Table 4 also, it shows the results of applying weight to Laws' masks filters. Additive Weighted Probability is a method where different weight had been applied towards Laws' masks filters. The weight applied represent how good a particular Laws' mask filters contribute to the process of recognition. Higher weight is given to the Laws' mask filter that achieve highest posterior probability and vice versa. From Table 4, the accuracy of applying weight is more higher compared to without considering any weight. This shows that weight given have impacted the ensemble of these Laws' masks filter.

Table 3
Accuracy for leaf recognition for Laws' Masks Filters

Experiment	1	2	3	4	5	6	7	8	9	10	Average	Std Dev
Original	0.8522	0.8722	0.8698	0.8448	0.8547	0.8716	0.8842	0.8547	0.8845	0.8473	0.8636	0.0147
L5L5	0.5394	0.5528	0.5848	0.5640	0.5296	0.5407	0.5197	0.5468	0.5381	0.5025	0.5418	0.0228
E5E5	**0.8793**	**0.8698**	**0.8845**	**0.8350**	**0.8719**	**0.8642**	**0.8670**	**0.8547**	**0.8845**	**0.8768**	**0.8688**	**0.0151**
S5S5	0.4310	0.4423	0.4300	0.4483	0.4138	0.4765	0.4187	0.4138	0.4521	0.4286	0.4355	0.0197
R5R5	0.6995	0.7764	0.7543	0.7044	0.7241	0.7506	0.7463	0.7537	0.7396	0.7340	0.7383	0.0236
W5W5	0.3916	0.3882	0.3784	0.3867	0.3793	0.3654	0.3645	0.3768	0.3661	0.3522	0.3749	0.0126
E5L5	0.8498	0.8600	0.8747	0.8498	0.8424	0.8691	0.8424	0.8719	0.8771	0.8670	0.8604	0.0134
W5L5	0.7980	0.8280	0.7887	0.8227	0.7931	0.8074	0.8374	0.8153	0.8256	0.8177	0.8134	0.0161
S5E5	0.8079	0.8501	0.8403	0.7586	0.8251	0.8173	0.8177	0.7882	0.8108	0.8227	0.8139	0.0258
R5L5	0.7783	0.8305	0.8084	0.7660	0.7685	0.8000	0.8227	0.7611	0.7936	0.8054	0.7934	0.0242
S5L5	0.8276	0.8403	0.8182	0.8153	0.8374	0.8691	0.8202	0.8473	0.8526	0.8498	0.8378	0.0175
W5E5	0.8054	0.8084	0.8157	0.7956	0.8079	0.8321	0.8030	0.8030	0.7961	0.7562	0.8023	0.0193
W5S5	**0.3990**	**0.4373**	**0.4300**	**0.3867**	**0.3768**	**0.4049**	**0.3670**	**0.3793**	**0.4177**	**0.3842**	**0.3983**	**0.0238**
R5E5	0.7118	0.7789	0.7396	0.7438	0.7635	0.7901	0.7783	0.7660	0.7494	0.7389	0.7560	0.0237
R5S5	0.3892	0.4472	0.4742	0.4113	0.4163	0.4148	0.3842	0.4064	0.3882	0.4236	0.4155	0.0280
W5R5	0.7069	0.6978	0.6757	0.6724	0.6970	0.7185	0.7414	0.7044	0.7322	0.6724	0.7019	0.0242

Table 4
Accuracy for leaf recognition for combination of Law Masks Filters

Experiment	Original	Additive Probability	Additive Weighted Probability
1	0.8522	0.9015	0.9064
2	0.8722	0.9042	0.9165
3	0.8698	0.9091	0.9115
4	0.8448	0.8768	0.8916
5	0.8547	0.8793	0.8941
6	0.8716	0.9185	0.9333
7	0.8842	0.9039	0.9015
8	0.8547	0.8990	0.9138
9	0.8845	0.9140	0.9287
10	0.8473	0.8966	0.9163
Average	0.8636	**0.9003**	**0.9114**
Std Dev	0.0147	**0.0135**	**0.0135**

4. Conclusion

As mentioned by Dash *et al.*, [22] and Dash and Jena [23], Laws' masks filters provide poor classification accuracy. Hence in this work, poor classification accuracy by Laws' masks filter have been helped by the ensemble of Laws' masks filters. The ensemble works in this experiment due to diversity [24] of each Law's masks filters. For a wide range of applications and in a variety of settings, ensemble based systems, also known as multiple classifier systems, committee of classifiers, or mixtures of experts, have proven to deliver better outcomes than single-expert systems [25]. In ensemble systems, a large number of classifiers are built and their outputs are combined so that the result outperforms the performance of a single classifier. However, this forces different classifiers to make errors in varied circumstances. The idea is that if each classifier has a unique error profile, then strategically combining these classifiers can lower the overall error. By combining all 15 Law's masks filters, the error is reduced and it helps to increase the recognition accuracy. Utilising sophisticated classifier techniques, such as deep learning, is another option to improve recognition accuracy. Future work can be looked at the application towards other type of images with more background challenges and more classes. This is to look at the robustness of the proposed method.

Acknowledgement
Our deepest gratitude and thanks to Universiti Teknikal Malaysia Melaka (UTeM) and the Ministry of Higher Education Malaysia for funding this research grant under Fundamental Research Grant Scheme (Grant no: FRGS/1/2020/ICT06/UTEM/02/1)).

References
[1] Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." *Frontiers in plant science* 7 (2016): 215232. https://doi.org/10.3389/fpls.2016.01419
[2] Golhani, Kamlesh, Siva K. Balasundram, Ganesan Vadamalai, and Biswajeet Pradhan. "A review of neural networks in plant disease detection using hyperspectral data." *Information Processing in Agriculture* 5, no. 3 (2018): 354-371. https://doi.org/10.1016/j.inpa.2018.05.002
[3] Lakshmanarao, A., M. Raja Babu, and T. Srinivasa Ravi Kiran. "Plant disease prediction and classification using deep learning ConvNets." In *2021 International Conference on Artificial Intelligence and Machine Vision (AIMV)*, pp. 1-6. IEEE, 2021. https://doi.org/10.1109/AIMV53313.2021.9670918
[4] Liu, Kangchen, and Xiujun Zhang. "PiTLiD: identification of plant disease from leaf images based on convolutional

neural network." *IEEE/ACM transactions on computational biology and bioinformatics* 20, no. 2 (2022): 1278-1288. https://doi.org/10.1109/TCBB.2022.3195291
[5] Jung, Minah, Jong Seob Song, Ah-Young Shin, Beomjo Choi, Sangjin Go, Suk-Yoon Kwon, Juhan Park, Sung Goo Park, and Yong-Min Kim. "Construction of deep learning-based disease detection model in plants." *Scientific reports* 13, no. 1 (2023): 7331. https://doi.org/10.1038/s41598-023-34549-2
[6] Omrani, Elham, Benyamin Khoshnevisan, Shahaboddin Shamshirband, Hadi Saboohi, Nor Badrul Anuar, and Mohd Hairul Nizam Md Nasir. "Potential of radial basis function-based support vector regression for apple disease detection." *Measurement* 55 (2014): 512-519. https://doi.org/10.1016/j.measurement.2014.05.033
[7] Ferentinos, Konstantinos P. "Deep learning models for plant disease detection and diagnosis." *Computers and electronics in agriculture* 145 (2018): 311-318. https://doi.org/10.1016/j.compag.2018.01.009
[8] Chen, Wen-Liang, Yi-Bing Lin, Fung-Ling Ng, Chun-You Liu, and Yun-Wei Lin. "RiceTalk: Rice blast detection using Internet of Things and artificial intelligence technologies." *IEEE Internet of Things Journal* 7, no. 2 (2019): 1001-1010. https://doi.org/10.1109/JIOT.2019.2947624
[9] Mishra, Sumita, Rishabh Sachan, and Diksha Rajpal. "Deep convolutional neural network based detection system for real-time corn plant disease recognition." *Procedia Computer Science* 167 (2020): 2003-2010. https://doi.org/10.1016/j.procs.2020.03.236
[10] Zamani, Abu Sarwar, L. Anand, Kantilal Pitambar Rane, P. Prabhu, Ahmed Mateen Buttar, Harikumar Pallathadka, Abhishek Raghuvanshi, and Betty Nokobi Dugbakie. "[retracted] performance of machine learning and image processing in plant leaf disease detection." *Journal of Food Quality* 2022, no. 1 (2022): 1598796. https://doi.org/10.1155/2022/1598796
[11] Zhang, Yan, Shiyun Wa, Longxiang Zhang, and Chunli Lv. "Automatic plant disease detection based on tranvolution detection network with GAN modules using leaf images." *Frontiers in Plant Science* 13 (2022): 875693. https://doi.org/10.3389/fpls.2022.875693
[12] Zhang, Shanwen, Xiaowei Wu, Zhuhong You, and Liqing Zhang. "Leaf image based cucumber disease recognition using sparse representation classification." *Computers and electronics in agriculture* 134 (2017): 135-141. https://doi.org/10.1016/j.compag.2017.01.014
[13] Amin, Muhammad Fikrun, Zuraini Othman, Sharifah Sakinah Syed Ahmad, and Fauziah Kasmin. "Analysis on the impact of imagenet preprocessing image mode using VGG19 pre-trained model in plant disease classification." *Proceedings of Mechanical Engineering Research Day* 2022 (2022): 154-155.
[14] Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." In *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, vol. 1, pp. 886-893. Ieee, 2005. https://doi.org/10.1109/CVPR.2005.177
[15] Zhang, Shanwen, Haoxiang Wang, Wenzhun Huang, and Zhuhong You. "Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG." *Optik* 157 (2018): 866-872. https://doi.org/10.1016/j.ijleo.2017.11.190
[16] Islam, Mohammad Aminul, Md Sayeed Iftekhar Yousuf, and M. M. Billah. "Automatic plant detection using HOG and LBP features with SVM." *Int. J. Comput* 33, no. 1 (2019): 26-38.
[17] Xia, Qing, Hao-Dong Zhu, Yong Gan, and Li Shang. "Plant leaf recognition using histograms of oriented gradients." In *International Conference on Intelligent Computing*, pp. 369-374. Cham: Springer International Publishing, 2014. https://doi.org/10.1007/978-3-319-09339-0_38
[18] Laws, Kenneth I. "Rapid texture identification." In *Image processing for missile guidance*, vol. 238, pp. 376-381. Spie, 1980. https://doi.org/10.1117/12.959169
[19] P. MISHRA, "Grapevine Disease Images." https://www.kaggle.com/datasets/piyushmishra1999/plantvillage-grape
[20] Novakovic, Jasmina Dj, Alempije Veljovic, Sinisa S. Ilic, Zeljko Papic, and Milica Tomovic. "Evaluation of classification models in machine learning." *Theory and Applications of Mathematics and Computer Science* 7, no. 1 (2017): 39-46.
[21] Hossin, Mohammad, and Md Nasir Sulaiman. "A review on evaluation metrics for data classification evaluations." *International journal of data mining & knowledge management process* 5, no. 2 (2015): 1. https://doi.org/10.5121/ijdkp.2015.5201
[22] Dash, Sonali, and Uma Ranjan Jena. "Multi-resolution Laws' Masks based texture classification." *Journal of applied research and technology* 15, no. 6 (2017): 571-582. https://doi.org/10.1016/j.jart.2017.07.005
[23] S. Dash and U. R. Jena, "Texture classification using Laws' filter in various color spaces," *Int. J. Eng. Technol.*, vol. 9, no. 2, pp. 454–460, 2017. https://doi.org/10.21817/ijet/2017/v9i2/170902305
[24] M. Astani, M. Hasheminejad, and M. Vaghefi, "A diverse ensemble classifier for tomato disease recognition," *Comput. Electron. Agric.*, vol. 198, no. October 2021, p. 107054, 2022.https://doi.org/10.1016/j.compag.2022.107054

[25] R. Polikar, "Ensemble based systems in decision making," *IEEE Circuits Syst. Mag.*, vol. 6, no. 3, pp. 21–44, 2006. https://doi.org/10.1109/MCAS.2006.1688199