NOVEL FEATURE EXTRACTION TECHNIQUES FOR GRAPE LEAF DISEASE DETECTION USING MACHINE LEARNING CLASSIFIERS

Prasad P S[1*], Dr. Blessed Prince P[2]

Abstract:
In the wide range of crops grown in India, fruits play a prominent role as it helps in good revenue for the farmers. Among them, the grape is extensively grown, as regular plants grapes also have various diseases that infect their fruits, stem and leaf that in turn affect yield. In the proposed work, diseases that infect leaves are considered such as fungi, viruses and bacteria and others are subjected to an automated disease detection algorithm. Automated disease detection will improve the diagnosis accuracy actions can be controlled more appropriately at the correct time. A widely employed method in these scenarios is, Image processing which is endorsed for leaf disease identification in plants and also helps in classification. Here, it is proposed to compare the algorithms that are categorized under supervised learning such as KNN and SVM that are implemented on image feature extraction techniques such as HOG, LBP and GLCM.

Index Terms: Grape disease diagnosis, KNN, SVM, HOG, LBP, GLCM

[1*]Presidency University/Computer Science & Engineering, Bengaluru, India,
Email: prasadps@presidencyuniversity.in
[2]Presidency University/Computer Science & Engineering, Bengaluru, India
Email: blessedprince@presidencyuniversity.in

***Corresponding Author:**Prasad P S
*Presidency University/Computer Science & Engineering, Bengaluru, India,
Email: prasadps@presidencyuniversity.in

DOI: - 10.48047/ecb/2023.12.4.267

1.Introduction

It is known for a long that the backbone of India is Agriculture and roughly 70% of the population is involved in agriculture directly or indirectly. In terms of land mass, the country is huge and it gives the farmers a wide range of options to choose the crops to grow, certainly along with this, diseases are also found on plants for which appropriate pesticides and insecticides have to be identified. As negligence of disease would result in the diminution of product quality and quantity in turn affecting the yield of the plants in turn returns of the farmer.

With the assistance of advanced technology, it has been capable to supply enough food for 7 billion people and to meet the demand new approaches are developed. Nevertheless, the food supply has been threatened by a lot of factors such as temperature, humidity, declination of natural pollinators and many more. Another threat that is observed as a part of food security is diseases in plants that can be resolved earlier by swift identification. Apart from food security, another major concern is a smallholder farmer's life which gets affected by the variation in the yield of the crop and could be completely disturbed. The overall agricultural production, around 80% of it is produced by smallholder farmers and it has been stated that yield loss of over 50% is because of pets and diseases. Adding to this, people from farming backgrounds and specifically smallholders account for 50% of the hunger index, this would be because of pathogens that cause interruptions in food supply [1].

However, it has remained a challenge to many research groups throughout the globe, for which one of the reasons would be the lack of the necessary framework. The disease of any plant can be studied based on the patterns that are visible on the plant. To successfully cultivate crops on the farm, along with the regular process, disease monitoring plays a crucial role. Currently, disease identification and detection are carried out by human intervention that is done by experts, when it has to be scaled a large expert team is required. More challenging is continuous monitoring, this results to be ineffective in terms of cost and therefore it is not scalable. On the other hand, apart from the facility the farmer lacks knowledge about contacting experts for solutions, the experts could also charge a lot of money and it also takes more time for analysis. To overcome the aforementioned drawbacks, the proposed alternative is automatic disease detection by observing the patterns on the leaves evident to be valuable, cost-effective and as well it is scalable to large farms.

Among the wide range of fruits that is grown in India, popular midst them is Grapes which cover an area of 155.30 thousand hectares occupying 2.24 % of the total area in 2020-21[2]. Importantly, it is grown for the purpose of winemaking and raisins, in India it is mainly consumed as fresh fruit. The reason behind the consumption of raisins or fresh grapes is the high nutrient content resulting in health benefits and also plays a prominent role as a natural remedy to solve several problems related to health. It can be observed that grape can be used extensively for a long-time span without being spoilt and with the health advantages it is grown extensively due to the ease of growing in flexible climatic situations and it has been evident to be profitable [3]. India is the 7th largest producer of grapes in the world, this is evident from the data obtained from 2016-2020, which accounts the 3.3% of the total world's grapes production. It is evident over two decades the area utilized for the growth of grapes has seen a considerable increase [4].

With the advantages, the grape crop is vulnerable to several diseases that seriously affect the yield of the crop. The intensity of any disease is inconsistent year on year, the possible solution for it to be identified in the earlier and exact identification disease helps in obtaining a high yield, reduces the losses and also helps with the proportion of pesticides that need to be used. Recognition of the disease appropriately is tough and the reason behind it is, identical symptoms for dissimilar diseases, dissimilar symptoms for the identical disease at distinct stages and lastly appearance of similar diseases at an instance of time [6]. Therefore, to overcome the oversights, an automated and robust approach is needed for identifying the disease more precisely. Among the existing diseases, three fungal diseases are considered here that has been crushing the output in most of the time. The diseases that are considered here are black rot, measles and leaf blight.

In the past ten years, machine learning has been fully explored and applied in fields like medicine, engineering, and e-commerce, as well as in applications like sign language recognition [7] and audio and visual speech recognition [8]. In the medical domain, multiple applications are realized including cancer detection in various parts of the body [9], [10]. Apart from this object [11], vehicle number plate detection [12], and alphanumeric identification are also performed.

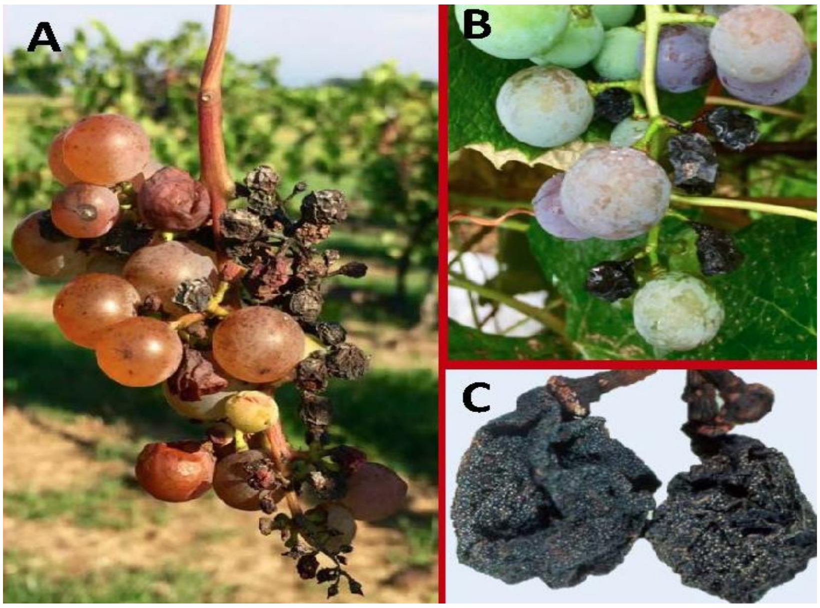

Fig 1: Stages of black rot disease (A) Various stages of black rot disease on a cluster at the same time. (B) Infected fruit shrivel and turn black. (C) Close-up of fruit mummies.

At the initial stage disease diagnosis and recognition are intended to assist the farmers so that it minimizes the utilization of pesticides, and shortens the ecological signature of pesticides, meanwhile increasing profits by reducing losses. To precisely identify the black rot, measles and leaf blight grape diseases at the initial stages, the following methodology is used:

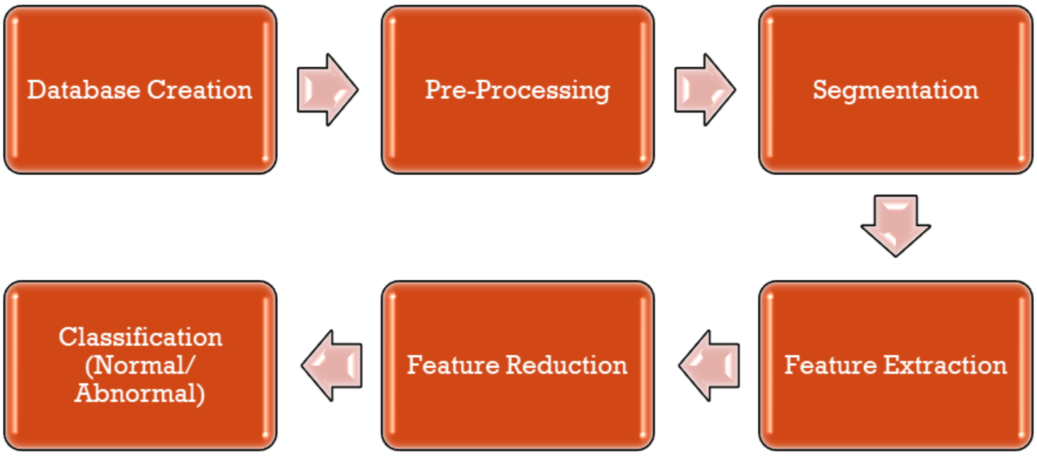

Fig 2: Block Diagram of Proposed Method

Here, the proposed work compares different types of object-identifying algorithms like Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM) these were implemented with "k-nearest neighbours" (kNN) and "Support Vector Machine" (SVM) which are supervised machine learning algorithms[29-40]. The data set that was considered was obtained from Kaggle.

2. Literature Review

Several automated attempts have been made in the recent past to identify the diseases in plants as well specifically on grapes, they are discussed below.

A combination of deep learning with fuzzy logic is proposed for disease detection in grapes. Images were segmented by implementing DeepLabV3+ and ResNet50 backbone. This method was specifically implemented to detect black measles. The aforementioned was part of the first step, as the next step, it included the calculation of the degree of damage the disease has caused. This also classified the leave's health into multiple grades healthy, mild, and medium severe. It was quantified in the manuscript that the total precision of the developed algorithm was 97.75%[13].

Even though multiple groups have developed several algorithms and implemented them for disease diagnosis in the recent past, for practical conditions more simplified techniques with the least possible information collected from the field. Here, a novel algorithm was developed for image computation [14]. Leaf diseases in grapes were identified such as black rot, blight and black measles. The area of interest is disease symptoms that is supposed to be partitioned from the healthy parts of the leaf. This was achieved by automatically applying k-means clustering, which helped in feature extraction in three non-identical colour models RGB, l*a*b and HSV. 98.71% of accuracy was reported by implementing the GLCM method. By employing principal component analysis (PCA) for the reduction in feature size and its accuracy was 98.97%.

Apart from python, neural networks can be implemented on MATLAB as well, a manuscript was published in which diseases presence or absence were spotted by an engaging convolutional neural network (CNN). This was implemented on Mango and Grape leaves with an accuracy rate of 89% and 99%. [15]. Python is an open-source hence, developing algorithms on the python platform would be more versatile.

CNN algorithms are resource-consuming therefore, light-weighted CNN models are proposed for grape disease detection by utilizing channel-wise attention (CA) method. The developed algorithm dataset was evaluated and accuracy was observed to be 99.14% [16]. Another CNN model is proposed by Ji. M et.al., in which united model was developed intended to distinguish the healthy leaf from the leaf affected with diseases such as black rot, esca and isariopsis leaf spot. The supplemental distinguishing features that were extracted here was possible by mixing multiple CNNS models, as a result presenting the capability of UnitedModel. The dataset employed here was PlantVillage and the United model, the models were evaluated based on these datasets and that was evaluated with the novel CNN models. It was evident that the validation accuracy was 99% and test accuracy was 98.57%[17].

Above mentioned approaches are time consuming, to complete the segmentation efficiently and quickly modified algorithms are required. Adeel A et. Al., proposed four step approach to identify the diseases in reduction of contrast haze called as LCHR, LAB color transformation as second step, canonical correlation analysis, in third step feature extraction by fusing canonical correlation analysis and lastly M-class SVM is performed on reduced features. The dataset that was used here was PlantVillage with three variations of diseases blackrot, measles and leaf blight. Rate of accuracy for segmentation was 90%v and 92% and above accuracy for classification [18].

As mentioned in the earlier sections that grape is grown vastly and even it is exported to neighbouring countries and to the middle east. Hence, to safeguard it from the diseases various pesticides are sprayed, with less knowledge and late recognition high quantity of pesticides will be used resulting in jeopardy on human health, this can be avoided by detecting the disease in early stage. Kolhalkar N.R et.al, proposed a MATLAB based system designed with virtue of mechatronics in which histogram analysis is involved. The models are developed to identified to identify disease namely Anthracnose, Powdery and Downey Mildew and automatically spray. Post disease detection, keeping philosophy of precision farming as reference automatically, this utilizes the pesticides economically and reduces its impact on living organisms including humans[19].

"Dual-channel Convolutional Neural Network" was employed by Harahap M et.al., to detect the diseases in grapes in which Gabor Filter method was implemented. A texture analysis was used here, in which Segmentation Based Fractal Co-Occurrence was used to pull out the data of leaves such as colour, texture and features. It is believed that a greater number of datasets would be directly proportional to the accuracy, but this would consume more time. Variation in test images angles and frequency values in Gabor approach would result in comprise of the accuracy of testing results. Aforementioned reasons would affect the DCCNN approach's accuracy[20].

Back propagation neural network (BPNN) along with analysis of images were implemented by Zhu J et.al. for detect grape diseases. To denoise the images in which disease were identified, on it Wiener-based Wavelet transforms was applied. For the enhancement of the lesion shape Otsu technique was implemented for segmentation and morphological models were used. For the comprehensive edge of lesion region Prewitt operator was implemented. Here, five leaf diseases anthracnose, leaf spot, Sphaceloma ampelinum de Bary, downy mildew and round spot were detected and to achieve this, five parameters such as area, circularity, shape complexity and rectangularity were drawn. It was evident that BPNN along with filtering method was capable to examine grape diseases with high classification accuracy[21].

The approaches are novel by implementing methods that are based on computer vision in which data segmentation is performed or dataset that is obtained from drones. The segmentation and classification of disease is complete only when it is identified correctly. Further, time taken to identify the disease is also very much important. Dwivedi R et.al., proposed a method in which a modified neural network called, "Grape Leaf Disease Detection Network (GLDDN)" was projected to diagnose the disease. In this, double observation method was implemented for classification, evaluation and detection of features. With this approach, it was reported that precision of GLDDN was 99.93% and it was intended to detect for esca, black-rot and isariopsis detection[22].

Several approaches are discussed here for grape disease detection but as the common data set is not used in all the test cases hence the comparison cannot be justified. Therefore, the authors here have implemented GLCM, HOG and LBP on kNN and SVM, all the combinations were simulated and their results were tabulated. This is discussed in detail in the following sections.

3. Implementation

In further sections the mathematical models of the approaches are discussed in detail that were implemented. Since, different methods are compared with the same data set, the result obtained from this approach will be more reliable. It is denoted in the flow chart below in figure 3.

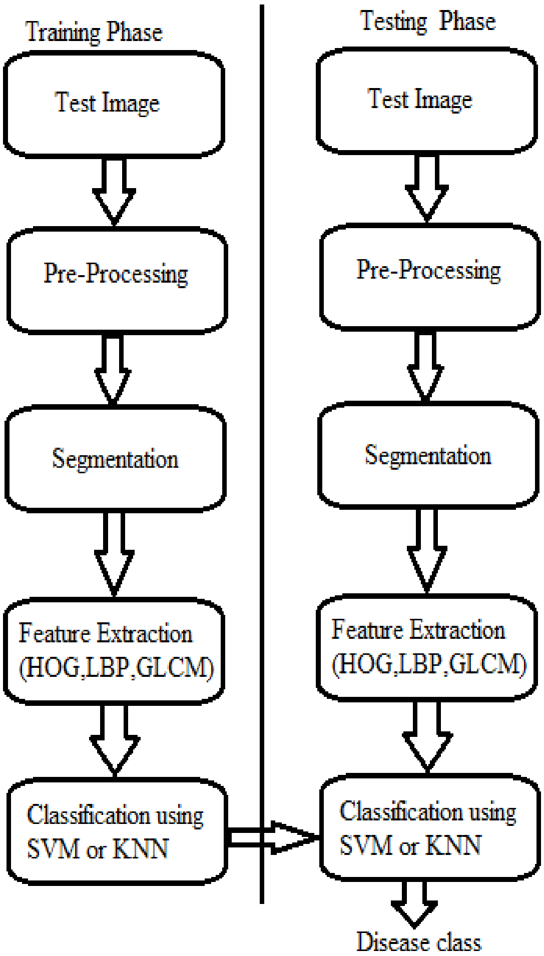

Fig 3: System Block Diagram

The steps involved in the implementation are discussed in detail:

A. Image Acquisition: In this procedure the specimen's photos are gathered; these are necessary to train the system. Photos of the leaves of Grape fruits are captured using camcorder, are used for both learning and investigating the device. The pictures are stored in jpg format that are applied for learning process. Few of the photographs are taken from cyberspace. Gathered photographs comprise the leaves that are unhealthy in plant disease.

B. Pre-processing: The images pre-processing is completed on accumulated images for enhancing the pictures aspect. This process isolates the background from the main image, further on it subdues the unwanted deformation. During this process, picture is initially rescaled to the dimension of 256x256. This project uses image processing with the goal of object detection, and one feature descriptor that may be used is the "Histogram of Oriented Gradients" (HOG). The technique counts occurrences of gradient orientation in localised portions of a picture.

C. Segmentation: An image needs to be sectioned or segmented to initialize the partition of the considered `picture into uniform sections with regard to specific features are completed. An approach in which enormous sets of data are gathered into small clusters or segments of the information that can be correlated. Images that are Gamma (γ) encrypted to improve the utilize the bits, post encryption of the picture, or bandwidth to transport a picture, by considering the advantage of the non-linear manner during which humans perceive light and colour. The red, green, and blue components of each pixel in an 8-bit RGB image are represented by a range of values, ranging from 0 to 255. A kernel creates a new image by performing simple mathematical operations on these pixel values.

D. Feature extraction: The characteristics that are pulled out are employed to the data that is not important of the given sample. The most sorts of characteristics that are considered are shape, colour and texture that are primarily employed in picture analysis method. For plant disease diagnosis, texture analysis characteristics must be involved. Therefore, in this analysis colour and texture characteristics pair were pulled out to urge enhance the precision. Further, sophisticated second-order boundary condition method that automatically identifies boundary with sub-pixel precision, utilizes the subsequent differential method of identifying zero intersections of second-order directional derivative within the gradient direction.

Subsequent stages are incorporated to determine the colour characteristics for a given image:

- Foremost transformation of RGB picture into HSV colour intervals are finished.
- A picture is partitioned into 3X3 blocks evenly.
- The average colour (H/S/V) for every of the nine block it is premeditated by implementing subsequent formula:

$$X' = \frac{1}{N} X^i$$

Where x_i stands for pixel concentration and N stands for the complete number of pixels. Here average is taken into account mutually of all the characteristics.

- The variance is calculated for each block using the equation below.

$$\mathrm{Variance} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{x_i} - \mathrm{x}')^2$$

The estimated variance has the power of calculating the variability.

- The asymmetry for every block of (H/S/V) is calculated. The asymmetry is employed to evaluate the picture's surface. Every block will have 3+3+3=9 colour characteristics.

$$\mathrm{Skewness} = \frac{\frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{x_i} - \mathrm{x}')^3}{(\frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{x_i} - \mathrm{x}')^2)^{\frac{3}{2}}}$$

The nine texture qualities—contrast, regularity, determined probability, similarity, diagonal variance, modification of variance, entropy, inverse difference, and nine characteristics of color—are used. Prior to employing a classifier like KNN or SVM, we must first combine the texture and colour (9+9=18) features for classification. The feature extraction techniques employed are LBP, HOG, and GLCM.

- **Local Binary Pattern (LBP):** It has been evident that the LBP method is cost effective and time required will be considerably less[23].

$$LBP(gp_x, gp_y) = \sum_{p=0}^{p-1} S(gp - gc) * 2^p$$

In the above equation, 'gp' is given by neighboring pixel's intensity with index p, and 'gc' is given by central pixel's intensity, 'p' is the number of sampling points on a circle of radius.

- **Histogram of Oriented Gradients (HOG):** In this method, in a localized portion of an image, occurrences are counted. Calculation of the image gradient is performed, which is obtained by combining the gradient and angle from the image, it is given by the below formulae[24].

For an instance if 3 x 3 image is taken, then for each pixel Gx and Gy are calculated

$$G_x(r, c) = I(r, c+1) - I(r, c-1)$$
$$G_y(r, c) = I(r-1, c) - I(r+1, c)$$

Magnitude and angle are calculated post calculation of G_x, and the formulae are given below:

$$Magnitude\ (\mu) = \sqrt{G_x^2 + G_y^2}$$

$$Angle\ (\theta) = \tan^{-1} \frac{G_x}{G_y}$$

- **Gray Level Co-occurrence Matrices (GLCMs):** These are used in the analysis in which texture studies are involved which can be observed in visual patterns. It has several features that are involved in GLCM calculation that includes energy, entropy, contrast, homogeneity, covariance, shade, and prominence and each of them are mathematically represented in its own format [25].

E. Classification: The methods that are used for classification are employed to identify the sort of plant disease. Classification trades with combining the considered input pattern with one amongst the definite class.

- **Support vector machines (SVM):** It is one among the most tough and precise algorithm in the available classifier [26]. The SVM equation is given below:

$$MAXIMIZE_{a_0+a_1 \ldots\ldots + a_m} : \sum_{j=1}^{n} MAX\{0,1 - (\sum_{i=0}^{m} a_i x_y + a_0) y_j\} + \lambda \sum_{i=0}^{m} (a_i)^2$$

- **K-nearest neighbor (KNN):** The other major classifier is KNN, that is intended to find the nearest neighbor for the unseen data point for a defined value of k[27].The class with the greatest number of data points among all classes of K neighbours will then be assigned to the unknown data point. The formulas are provided by for calculating the distance metrics:

$$d(x, x') = \sqrt{(x_1 - x_1')^2 + \cdots \ldots (x_n - x_n')^2}$$

Finally, the class with the highest probability is received by input x.

$$P(y = j | X = x) = \frac{1}{k} \sum_{i \in A} I(y^i = j)$$

The major challenges that are observed in implementing in this is overfitting and underfitting problem. Underfitting is caused when the developed model is inefficient to capture the underlying trend of data, resulting in bad performance on the test data set, however it will perform best on the training data set which do not serve the purpose. Similarly, in overfitting during the training the model learns from the noise and inappropriate data. Hence, this model fails to categorize data perfectly and the reason behind it is too many details and the noise. Therefore, care has to be taken to avoid both the conditions.

4. Results and Discussion

Training and testing with either classifier are the two stages of classification. A classifier is built

utilising feature values and the corresponding target values during the training phase. The classification of test imagery is then done using the trained classifier. 95 percent of the total images were used for training, while the final 5 percent were used for testing.
The performance of the model's capacity to categorize is defined by the confusion matrix by visualizing and summarizing. This also helps in understanding the type of the errors that are made during the development of the model. This was tested and implemented on all three-feature extractions and classification. 0, 1 and 2 are the numbers that denote the grape diseases, 0 stands for black rot, 1 stand for
measles and 2 stands for leaf blight.
Initially, the results of the SVM classifier are discussed.

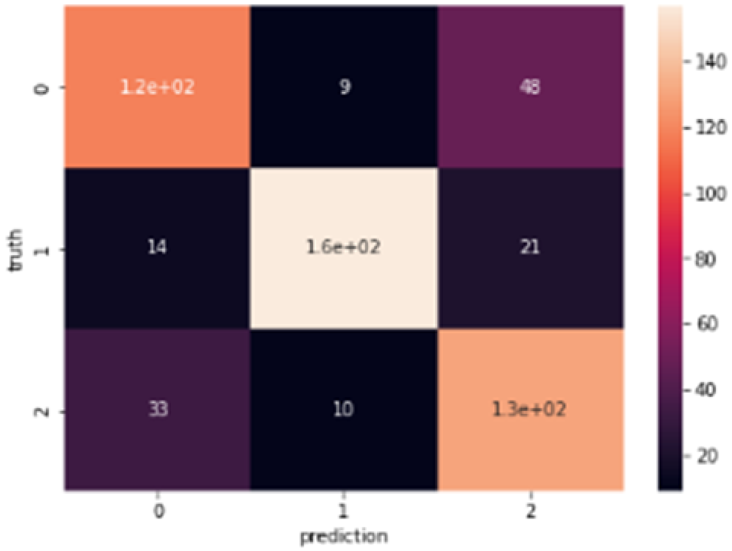

Fig 4 (a) Confusion matrix of LBP

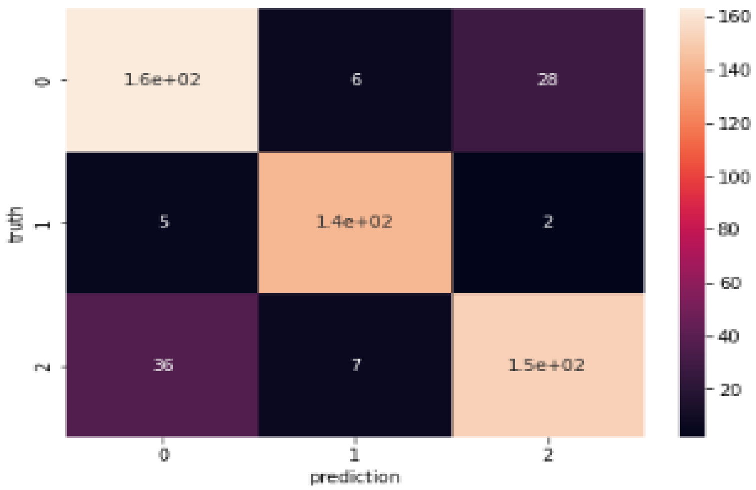

Fig 4 (b) Confusion matrix of HOG

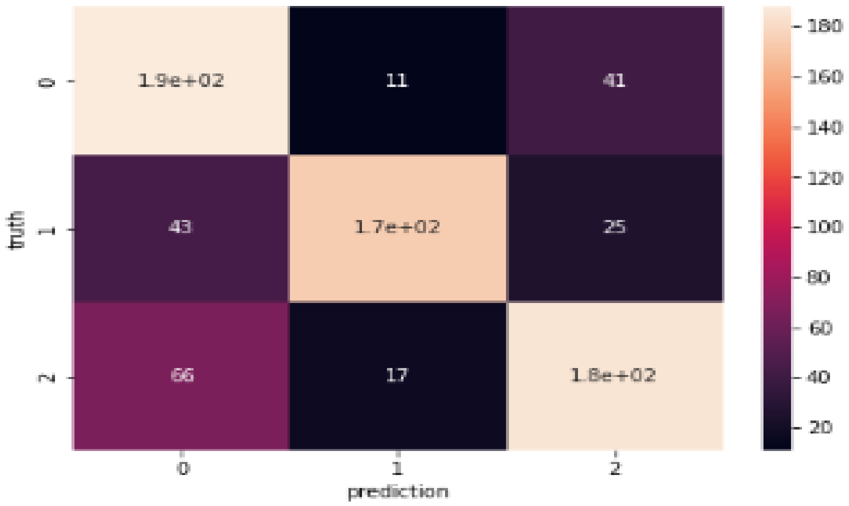

Fig 5 (a) Confusion matrix of LBP

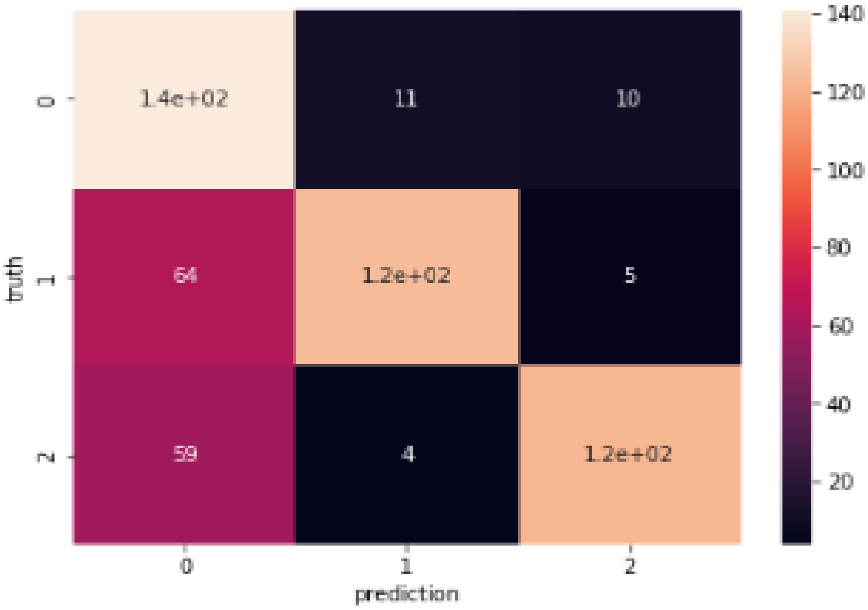

Fig 5 (b) Confusion matrix of HOG

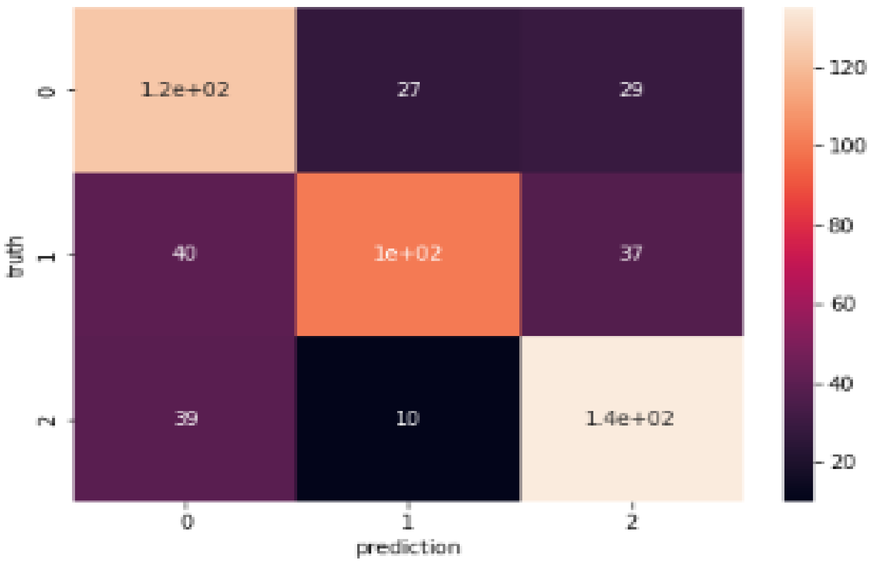

Fig 5 (c) Confusion matrix of GLCM

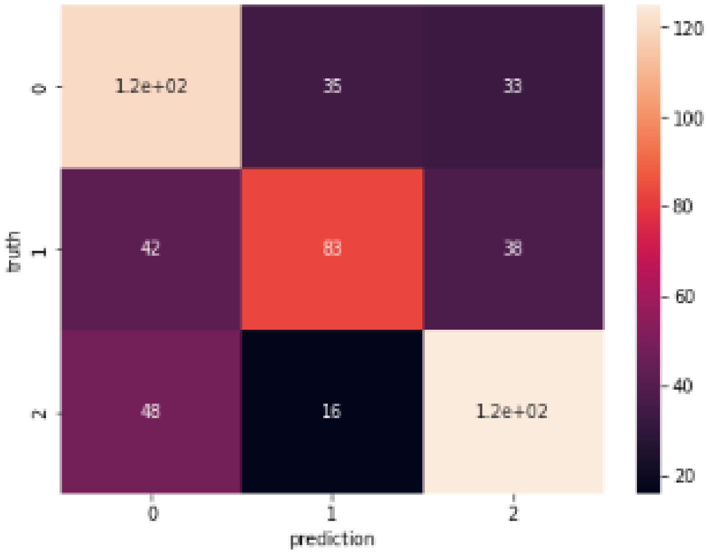

Fig 4 (c) Confusion matrix of GLCM

The results of the KNN classifier are discussed. It can be observed that the errors are observed to be less.

Accuracy of the testing sets is tabulated below in the graphical manner for SVM method.

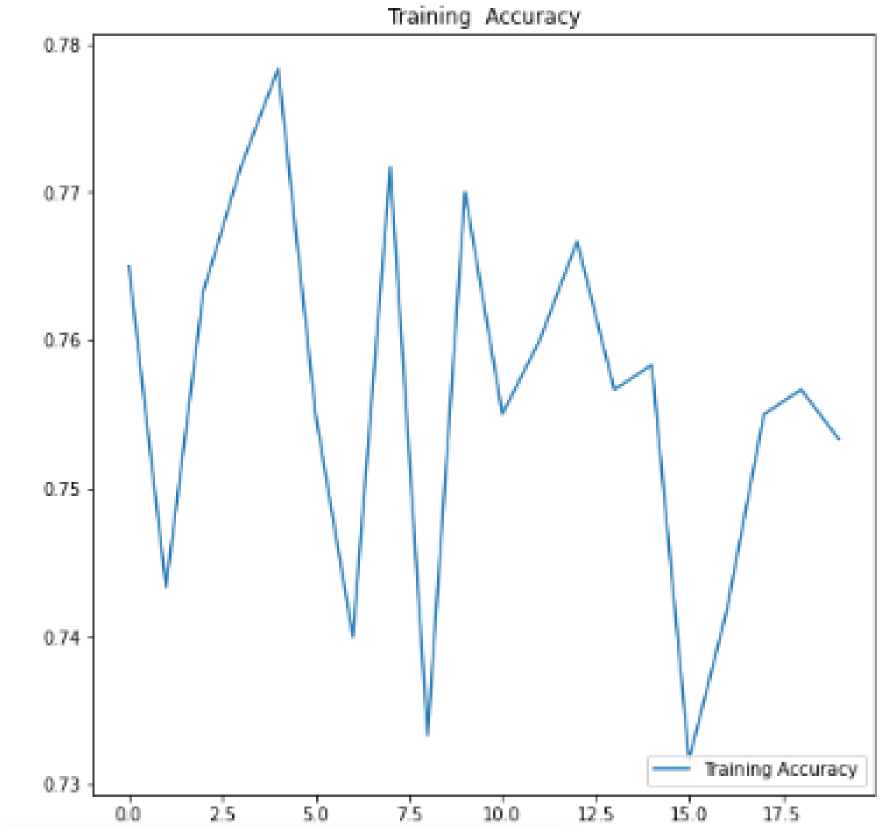

Fig 6 (a) Accuracy curve of LBP

Fig 6 (b) Accuracy curve of HOG

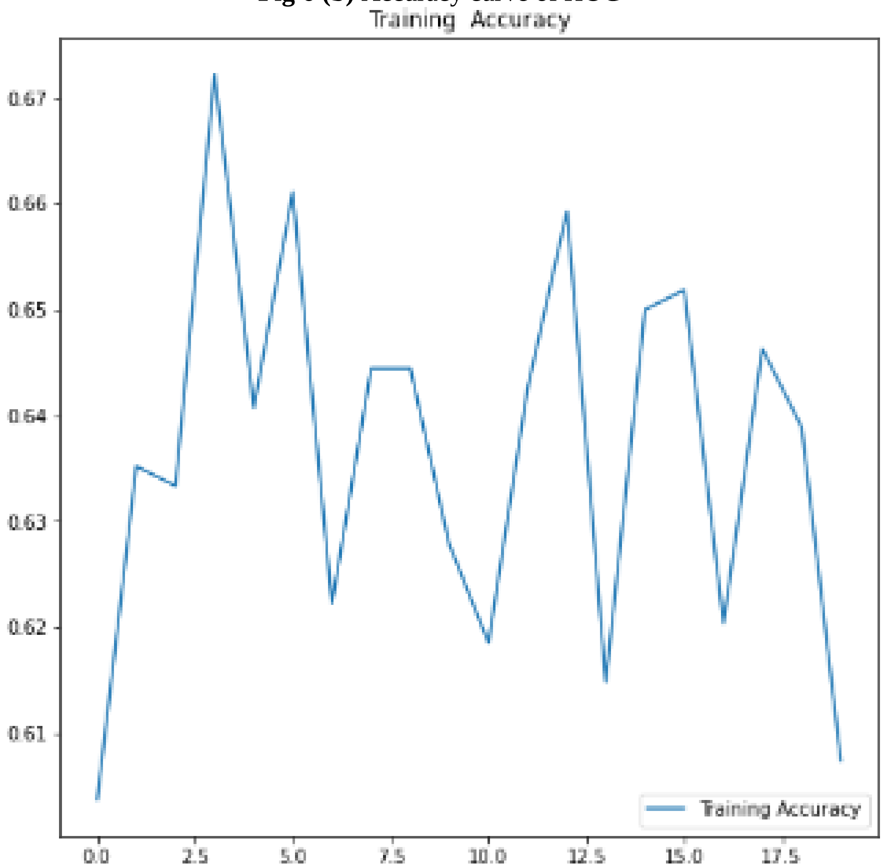

Fig 6 (c) Accuracy curve of GLCM

Accuracy of the testing sets is tabulated below in the graphical manner for KNN method.

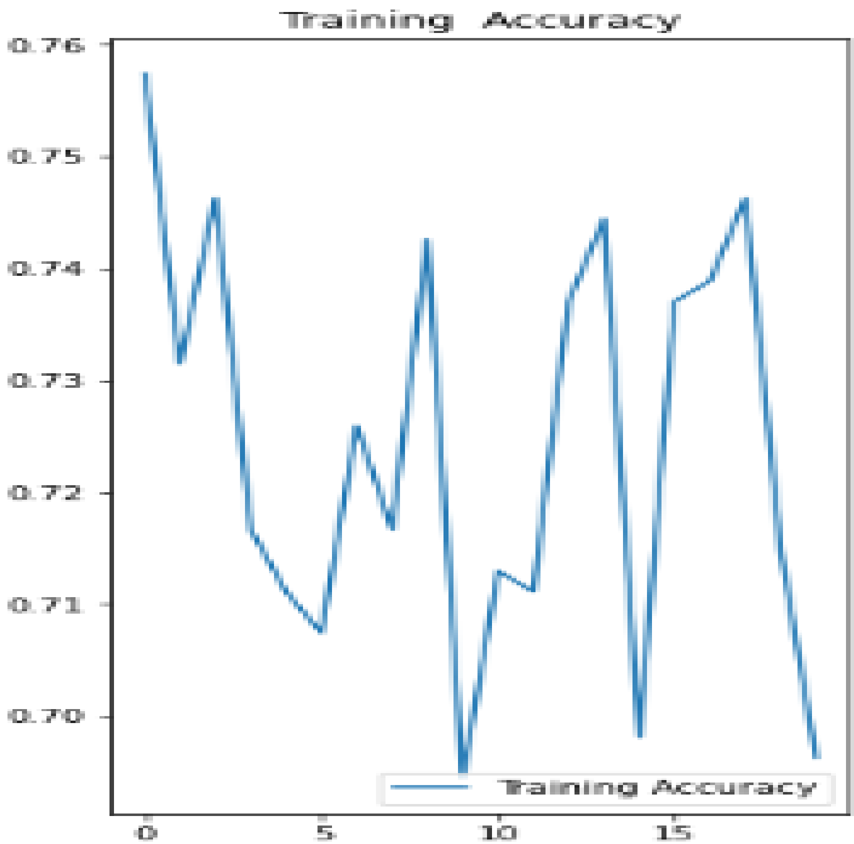

Fig 7 (a) Accuracy curve of LBP

Fig 7 (b) Accuracy curve of HOG

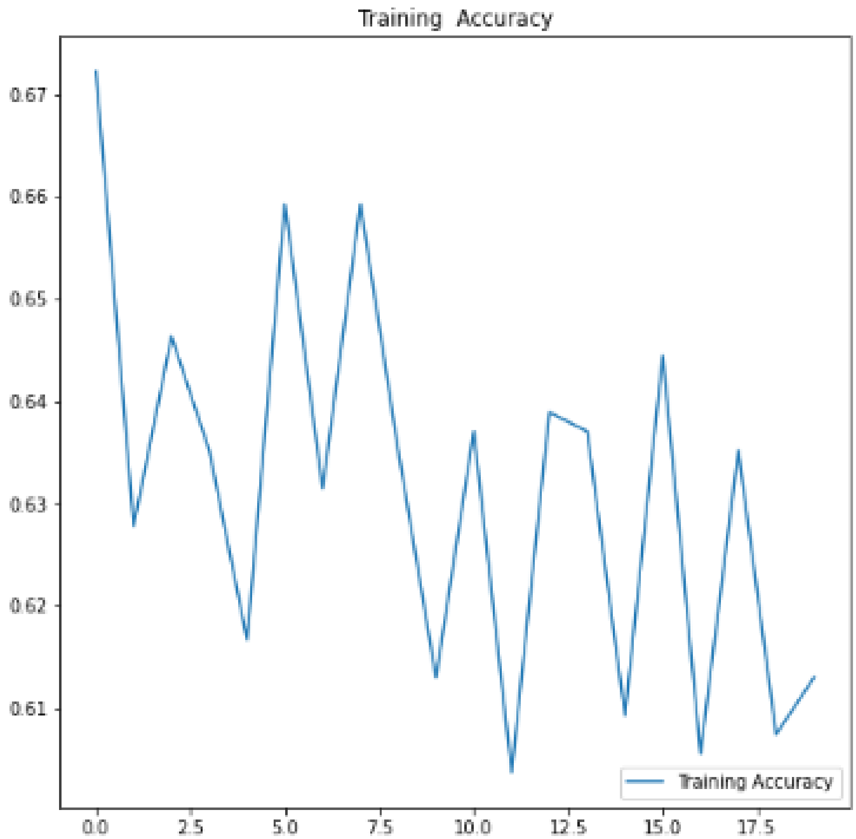

Fig 7 (c) Accuracy curve of GLCM

The test accuracy obtained for the feature extraction and classifier is mentioned in table 1. Precision and recall are the two metrics that are combined into a single number using a formula and it is called as F1-score which has importance in machine learning. This plays an important role in model evaluation along with accuracy.

Table 1: Accuracy, F1-score of the models

Classifier	Feature Extraction	Accuracy	F1-score
SVM	LBP	75%	0.77
	HOG	84%	0.86
	GLCM	61%	0.63
KNN	LBP	73%	0.74
	HOG	74%	0.76
	GLCM	66%	0.67

These are the test results obtained for the models that are not optimized, hence the accuracy is less than the literature mentioned in the survey.

5. Conclusion

As the main challenge to many research groups throughout the globe for which one of the reasons would be the lack of the necessary framework for detecting the diseases in various plants. A good framework or technique is necessary for any agriculture along with the traditional methods of farming. Hence in this context, disease monitoring plays a crucial role in agriculture. In this paper, we have carried out the comparison of various feature extraction algorithms and techniques such as LBP, HOG and GLCM and the classifiers are KNN and SVM. Based on the results obtained for various methods enumerated in Table 1, It is evident that HOG with SVM is more accurate compared to the other methods, and hence this method would be suitable for disease detection in grape plants.

References

1. R. Chand, P. Joshi, and S. Khadka, *Indian Agriculture Towards 2030: Pathways for Enhancing Farmers' Income, Nutritional Security and Sustainable Food and Farm Systems*. Springer Nature, 2022.
2. A. and P. F. P. E. D. A. of INDIA, "GRAPES RTI," *Ministry of Commerce and Industry, Government of India*, 2021. https://apeda.gov.in/apedawebsite/SubHead_Products/Grapes.htm#:~:text=India Facts and Figures %3A,fresh Grapes to the world.
3. B. Sandika, S. Avil, S. Sanat, and P. Srinivasu, "Random forest based classification of diseases in grapes from images captured in uncontrolled environments," in *2016 IEEE 13th International Conference on Signal Processing (ICSP)*, 2016, pp. 1775–1780. doi: 10.1109/ICSP.2016.7878133.
4. Wikipiedia, "List of countries by grape production," *The Wikimedia Foundation*, 2021. https://en.wikipedia.org/wiki/List_of_countries

_by_grape_production

5. N. GRAPES, "Grape profile," *Indian Counc. Agric. Res.*, 2006.
6. C. A. and A.-F. Canada, O. Carisse, and des pêcheries et de l'alimentation Québec (Province). Ministère de l'agriculture, *Identification Guide to the Major Diseases of Grapes [electronic Resource]*. Agriculture and Agri-Food Canada, 2006.
7. M. Safeel, T. Sukumar, K. S. Shashank, M. D. Arman, R. Shashidhar, and S. B. Puneeth, "Sign Language Recognition Techniques- A Review," 2020. doi: 10.1109/INOCON50539.2020.9298376.
8. R. Shashidhar, S. Patilkulkarni, and S. B. Puneeth, "Combining audio and visual speech recognition using LSTM and deep convolutional neural network," *Int. J. Inf. Technol.*, 2022, doi: 10.1007/s41870-022-00907-y.
9. W. Bulten *et al.*, "Artificial intelligence for diagnosis and Gleason grading of prostate cancer: the PANDA challenge," *Nat. Med.*, vol. 28, no. 1, pp. 154–163, 2022, doi: 10.1038/s41591-021-01620-2.
10. A. B. Nassif, M. A. Talib, Q. Nasir, Y. Afadar, and O. Elgendy, "Breast cancer detection using artificial intelligence techniques: A systematic literature review," *Artif. Intell. Med.*, vol. 127, p. 102276, 2022, doi: https://doi.org/10.1016/j.artmed.2022.102276.
11. S. Dolnicar *et al.*, "Infrastructure-based object detection and tracking for cooperative driving automation: A survey," *Annals of Tourism Research*, vol. 3, no. 1. pp. 1–2, 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0160738315000444
12. R. Shashidhar, A. S. Manjunath, R. Santhosh Kumar, M. Roopa, and S. B. Puneeth, "Vehicle Number Plate Detection and Recognition using YOLO- V3 and OCR Method," in *2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, 2021, pp. 1–5. doi: 10.1109/ICMNWC52512.2021.9688407.
13. M. Ji and Z. Wu, "Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic," *Comput. Electron. Agric.*, vol. 193, p. 106718, 2022, doi: https://doi.org/10.1016/j.compag.2022.106718.
14. S. M. Javidan, A. Banakar, K. A. Vakilian, and Y. Ampatzidis, "Diagnosis of grape leaf diseases using automatic K-means clustering and machine learning," *Smart Agric. Technol.*, vol. 3, p. 100081, 2023, doi: https://doi.org/10.1016/j.atech.2022.100081.
15. U. Sanath Rao *et al.*, "Deep Learning Precision Farming: Grapes and Mango Leaf Disease Detection by Transfer Learning," *Glob. Transitions Proc.*, vol. 2, no. 2, pp. 535–544, 2021, doi: https://doi.org/10.1016/j.gltp.2021.08.002.
16. Z. Tang, J. Yang, Z. Li, and F. Qi, "Grape disease image classification based on lightweight convolution neural networks and channelwise attention," *Comput. Electron. Agric.*, vol. 178, p. 105735, 2020.
17. M. Ji, L. Zhang, and Q. Wu, "Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks," *Inf. Process. Agric.*, vol. 7, no. 3, pp. 418–426, 2020.
18. A. Adeel *et al.*, "Diagnosis and recognition of grape leaf diseases: An automated system based on a novel saliency approach and canonical correlation analysis based multiple features fusion," *Sustain. Comput. Informatics Syst.*, vol. 24, p. 100349, 2019.
19. N. R. Kolhalkar and V. L. Krishnan, "Mechatronics system for diagnosis and treatment of major diseases in grape vineyards based on image processing," *Mater. Today Proc.*, vol. 23, pp. 549–556, 2020.
20. M. Harahap, V. Angelina, F. Juliani, and O. Evander, "Grape disease detection using dual channel Convolution Neural Network method," *Sink. J. dan Penelit. Tek. Inform.*, vol. 5, no. 2, pp. 314–324, 2021.
21. J. Zhu, A. Wu, X. Wang, and H. Zhang, "Identification of grape diseases using image analysis and BP neural networks," *Multimed. Tools Appl.*, vol. 79, no. 21, pp. 14539–14551, 2020.
22. R. Dwivedi, S. Dey, C. Chakraborty, and S. Tiwari, "Grape disease detection network based on multi-task learning and attention features," *IEEE Sens. J.*, vol. 21, no. 16, pp. 17573–17580, 2021.
23. M. Harmouch, "Local Binary Pattern Algorithm: The Math Behind It," *The Startup*, 2020. https://medium.com/swlh/local-binary-pattern-algorithm-the-math-behind-it-□-edf7b0e1c8b3
24. M. Tyagi, "HOG (Histogram of Oriented Gradients): An Overview." https://towardsdatascience.com/hog-histogram-of-oriented-gradients-67ecd887675f
25. B. E. Park, W. S. Jang, and S. K. Yoo, "Texture analysis of supraspinatus ultrasound image for computer aided diagnostic system," *Healthc. Inform. Res.*, vol. 22, no. 4, pp. 299–304, 2016.

26. T. Shin, "A Mathematical Explanation of Support Vector Machines," *Towards Data Science*, 2021. https://towardsdatascience.com/a-mathematical-explanation-of-support-vector-machines-e433ffe04362
27. I-king-of-ml, "KNN(K-Nearest Neighbour) algorithm, maths behind it and how to find the best value for K," *Medium*, 2019.
28. P. B. Padol and S. D. Sawant, "Fusion classification technique used to detect downy and Powdery Mildew grape leaf diseases," 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC), Jalgaon, India, 2016, pp. 298-301, doi: 10.1109/ICGTSPICC.2016.7955315.
29. G. Sabarmathi and Dr.R. Chinnaiyan, "Reliable Machine Learning Approach to Predict Patient Satisfaction for Optimal Decision Making and Quality Health Care," *2019 International Conference on Communication and Electronics Systems (ICCES)*, Coimbatore, India, 2019, pp. 1489-1493.
30. G. Sabarmathi and Dr.R. Chinnaiyan, "Big Data Analytics Framework for Opinion Mining of Patient Health Care Experience" International Conference on Computing Methodologies and Communication (ICCMC 2020), IEEE Xplore Digital Library
31. G. Sabarmathi and R. Chinnaiyan, "Reliable feature selection model for evaluating patient home health care services opinion mining systems," *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 2021, pp. 1-4
32. G.Sabarmathi , Dr.R.Chinnaiyan (2018), "Envisagation and Analysis of Mosquito Borne Fevers – A Health Monitoring System by Envisagative Computing using Big Data Analytics" in ICCBI 2018 – Springer on 19.12.2018 to 20.12.2018
33. G.Sabarmathi, Dr.R.Chinnaiyan *"Mining Patient Health Care Service Opinions for Hospital Recommendations"* International Journal of Engineering Trends and Technology 69.9(2021):161-167
34. Hari Pranav A;M. Senthilmurugan;Pradyumna Rahul K;R. Chinnaiyan , "IoT and Machine Learning based Peer to Peer Platform for Crop Growth and Disease Monitoring System using Blockchain," *2021 International Conference on Computer Communication and Informatics (ICCCI)*, 2021, pp. 1-5.
35. M. Latha, M. Senthilmurugan and R. Chinnaiyan, "Brain Tumor Detection and Classification using Convolution Neural Network Models," *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 2021, pp. 1-5.
36. M. Senthilmurugan, M. Latha and R. Chinnaiyan, "Analysis and Prediction of Tuberculosis using Machine Learning Classifiers," *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 2021, pp. 1-4.
37. Preetika B, ; M. Latha; M. Senthilmurugan; R. Chinnaiyan, , "MRI Image based Brain Tumour Segmentation using Machine Learning Classifiers," *2021 International Conference on Computer Communication and Informatics (ICCCI)*, 2021, pp. 1-9.
38. R. Chinnaiyan and D. Stalin Alex, "Early Analysis and Prediction of Fetal Abnormalities Using Machine Learning Classifiers," 2021 2nd International Conference on Smart Electronics andCommunication(ICOSEC),2021,pp.1764-1767.
39. R. Chinnaiyan and S. Alex, "Machine Learning Approaches for Early Diagnosis and Prediction of Fetal Abnormalities," 2021 International Conference on Computer Communication and Informatics (ICCCI), 2021, pp. 1-3.
40. R.Chinnaiyan, Dr.Stalin Alex (2021). Optimized Machine Learning Classifier for Early Prediction of Fetal Abnormalities . International Journal of Computational Intelligence in Control 13(2)