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Machine Learning Based Massive Leaf Falling Detection For Managing The Waste Disposal Efficiently

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Abstract: Massive falling of leaves in dense tree region during autumn environment often creates huge collection of waste each year. To maintain and manage a clean environment, it is necessary to collect the dried leaf waste regularly at rapid intervals. In order of claiming this, it is very essential to development a leaf falling simulator using objective detection principle that measures the size of the leaf, color and other relevant features for efficient feature selection, detection and collection of waste. In order to accommodate these three tasks, the study uses a machine learning detection that essentially identifies the leaves based on input datasets. The study considers various input features like size of the leaf, color, falling rate of a dried leaf and moment of inertia. These features are utilized for detecting the falling leaves and providing the input for clearing the leaf waste in that region. The experiments are conducted to test the real-time applicability of the model against various trees and in different regions.

Keywords:
Leaf fall detection, Machine Learning, Detection, Feature extraction

1. INTRODUCTION

In recent years, municipalities have increased their participation in waste management to boost environmental performance through waste recovery. There are two phases in a typical waste management system. First phase is the collection of waste from houses for

transportation to the nearest waste transportation centre (WTC). Domestic garbage, which is usually collected by truck to transfer to the WTC, is classified as corresponding waste containers in front of residents' homes.
The second stage is the transfer of waste, on the basis of its classification, from WTC to the nearest waste disposal station. [1] [18] [20].
This method is related to complex activities, such as road and scheduling, and can include various choices. This led to research into the best position of collection centres, the ability of containers in each recall centre and waste storage at WTC. This research was conducted. The optimal transport route for domestic waste from each WTC to the waste disposal station is another main problem [21]-[23].

Machine learning helps computers to learn from interactions and examples without human intervention or explicit programming. Automation is a key component of the product and the need for AI rapidly quick in machine learning, as it is the key to artificial intelligence and deep learning in today's world. It can also be used extensively in the field of waste detection, as it plays a key role in many fields.

The classification of areas that have waste [8]–[10] and clean areas is increasingly relevant, given the fact that municipal vehicles frequently spend their time in areas that are already clean and therefore waste significant quantities of fuel, manpower and areas that really need to be cleaned. So it will enable the authorities to obtain production output if any device detects and classifies the areas as clean and with waste[2].
In this paper, we detect the massive falling of leaves in dense tree region during autumn environment, since it creates huge collection of waste each year. To maintain a clean environment, it is necessary to collect the dried leaf waste regularly at rapid intervals.
The main contribution of the work involves the following:

- The authors develop a machine learning based leaf falling detector using objective detection principle that measures the size of the leaf, color and other relevant features for efficient feature selection, detection and collection of waste.
- The study tends to accommodate these three tasks, the study uses a machine learning detection that essentially identifies the leaves based on input datasets. It considers various input features like size of the leaf, color, falling rate of a dried leaf and moment of inertia. These features are utilized for detecting the falling leaves and providing the input for clearing the leaf waste in that region.
- The experiments are conducted to test the real-time applicability of the model against various trees and in different regions.

2. RELATED WORKS

De Carolis, et al. [3] focused on creating a programme that can identify and monitor waste presence in real time by analysing video streams. In order to identify and recognise waste, an enhanced YOLOv3 network model is used. The network has been configured for this purpose on a collected data collection.
Wu, Z., et al. [4] investigated the waste classification situation in college and university. This paper proposes feasible management modes and suggestions on the classification of college household wastes by study of the identification, involvement and help of college student waste classification.

Donati, L., et al. [5] proposedan automated system of waste identification for traffic, capable of identifying and correctly instructing road haulers to manage most forms of waste. With this easy addition to an already available sweeper, the cleaning systems can reduce brush fatigue by more than 80 percent and reduce brush wear by the same amount (prolonging their lifetime). This is achieved by deciding when to use the pins, how much power to use and where to use them.

Meng, C. Y., & Sheng, Y. D. [6] developed a small waste sweeper built in view of the difficulty in sweeping the leaves and the waste in the lawns. In order to automatically purify and recycle waste, the engine powers the cleaning roller and the moving mechanics. In order to complete the preliminary waste screening, the author installed a filter component and a recycling unit in the recycling bin.

Kang, Z., et al. [7] proposed automated waste classification method that focused on profound learning. Firstly, the entire waste bin system, including the hardware and mobile application, is planned. Secondly, the proposed waste classification algorithm relies on ResNet-34 and is further optimised in three ways, namely the multi-functional merging of the input images, the residual feature reutilization unit and the creation of a new activation feature.

3. PROPOSED METHOD

The proposed method involves the detection of leaf falling in a video stream using three different machine learning models and thereby allowing the decisions to trucks for collecting the garbage or not.

Step 1: The process involves conversion of color to gray conversion, background noise removal and background object removal. All these three constitutes to form a preprocessing operation.

Step 2: Secondly, feature extraction of leafs are carried out using Log-Gabor Filter extracts the leaf and then provides the decision to the classification or detection engine.

Step 3: Thirdly, classification engine with machine learning algorithms namely k-nearest classifier, Naïve Bayes and Support Vector Machine (SVM). The classifier is initially trained with the leaf samples.

Step 4: Classifier is supplied with real time videos to detect the falling leaf and finding the accuracy of fall detection based on the parameters like leaf size, color, falling rate and moment of inertia.

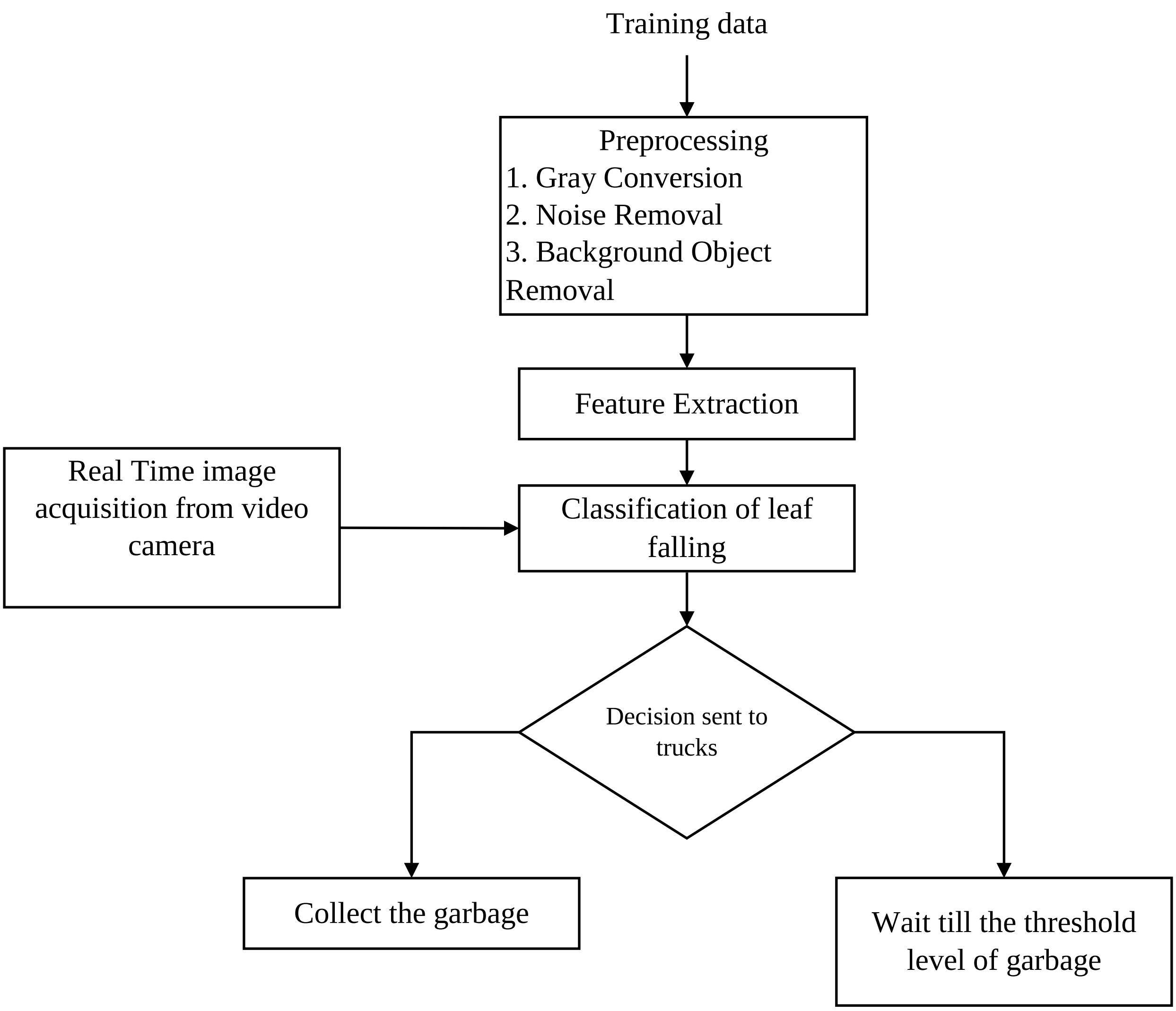

Figure 1: Architecture on leaf falling detection and garbage collection

Noise Removal:

A significant part of digital image processing is part of image restauration. Imaging restore is a method of deterioration that happens during the image capture. Sound and blurring are caused by deterioration by electronic and photometric sources. Blurring reflects a reduction in the bandwidth of images from an incomplete image building procedure, such as relative movement between the camera and the scene or a blurred optical device. Noise is the unwanted signal that degrades the visual quality of the digital images. Imperfect devices, data acquisition process issues, natural interference, transmission and compression are the principal sources of noise in digital images. Imaging is a pre-processing stage in the fields of image, testing, technologies and medical science in which the pictures have been deteriorated and have to be reconstructed before further processing. Total Adaptive Edge Variation Denoising is one of the noise reduction strategies used by this proposed method.

Background Object Removal

Segmenting images into various regions with identical attributes for each pixel. The regions should have a clear connection with the artefacts or characteristics mentioned that are important and useful for the analysis and the interpretation of photographs. Segmentation is the first step in a low level image processing to translate a grey or coloured image into one or more other images in terms of features, objects and scenes in a high-level image definition.

The performance of the image analysis depends on the segmentation reliability, but a precise partitioning of the image is often very difficult.

Feature Extraction using Log-Gabor Filter:

The filters are used to extract the leaf features depending on the size and colour of the image training datasets. One of the disadvantages of a Gabor filter, however, is that when its bandwidth is larger than an octave, the also symmetrical filter has a DC component. If you want large spectral information with maximum spatial position, Gabor filters are not optimal. A Log-Gabor Filter from Field is used to solve this limitation by eliminating the DC component. This filter allows the output of zero DC components for any bandwidth. The arbitrary bandwidth Log-Gabor filter can be built to build a filter with a limited range. The Log-Gabor filter's frequency response is:

$$G\left(f\right)=\exp\left[\frac{-\left(\log\left(\frac{f}{f_0}\right)\right)}{2\left(\log\left(\frac{\sigma}{f}\right)^2\right)}\right] \tag{1}$$

wheref_0- centre frequency and σ – filter bandwidth.

Detection of Leaf falling using ML classifiers

Classification takes into account the moment of inertia of leaf falling and the gravitational force to estimate the fall of leaf from the incoming video stream.

The entire leaf dropping motion can be interpreted as the combination of several primitive movements, while the switches are not arbitrary between those primitive movements. The combination of the required speed and angular speed provides an initial motion direction for a falling leaf. This is stored in a dataset.

Classifying objects is a simple task for humans, but it has proved to be difficult for computers. In addition to the growing requirements of automated video analytics, the computer and the high-end and cheap video cameras created interest in algorithms for the classification of objects. An easy classification system consists of a camera placed high above the zone for the processing and recording of the images.

Classification requires image sensors, pre-processing, object detection and division, feature removal and object classification. Classification systems are a database of predetermined leaf patterns to be categorised in contrast to the detected objects Classification systems. The proposed system is used by three separate learning engine algorithms to identify the dropping leaves, namely, KNN [11], NB [12] and SVM [13].

4. RESULTS AND DISCUSSIONS

In this section, all the three classifiers are tested with different leaf falling videos to test the efficacy of the system. The testing is carried out in terms of accuracy and computational time. The accuracy of the leaf falling detection defines how accurately the system detects the falling leaves after training. The computational time is defined as the total time taken by the system for training and testing the video and provides signal to the truck for garbage collection or not.

The Table 1 shows the results of feature extraction module that consists of Log-Gabor filter with three different leaf falling videos for training and testing the classifier. The results are varying for three different videos and the PSNR level is found higher in all the video that signifies the optimal extraction of leaf features from the input images. The other metrics like SNR, MSE and SSIM claims optimal leaf feature extraction from input images.

Table 1:Comparison of Log-Gabor filter for Video-1,2,3

Video	**Training/ Testing**	**PSNR**	**SNR**	**MSE**	**SSIM**
Video 1	Training	11.2771	24.1840	46.3726	0.9608
Video 2	Training	12.8862	23.3971	50.8637	0.9544
Video 3	Training	14.5966	22.7012	57.4882	0.9670
Video 1	Testing	10.8346	25.0751	49.6556	0.9620
Video 2	Testing	11.0053	23.3330	36.1042	0.9827
Video 3	Testing	11.6307	24.7662	52.0606	0.9582

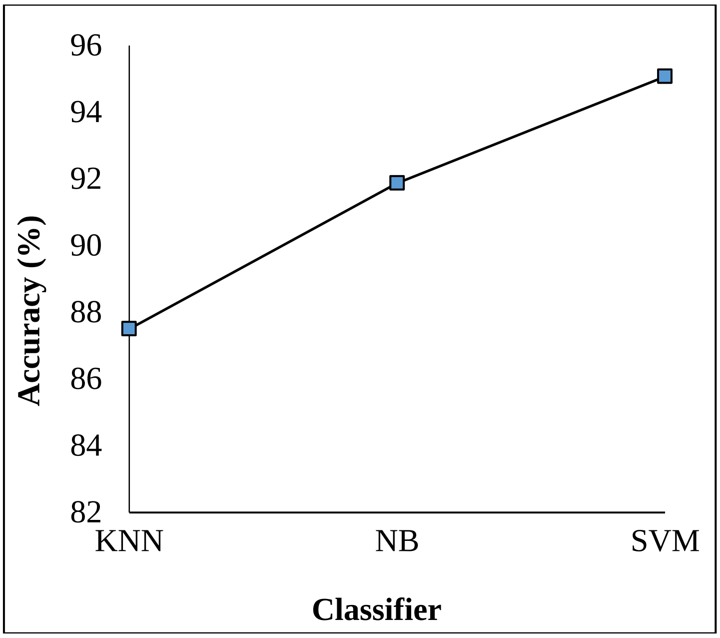

Figure 2: Accuracy in % for video 1

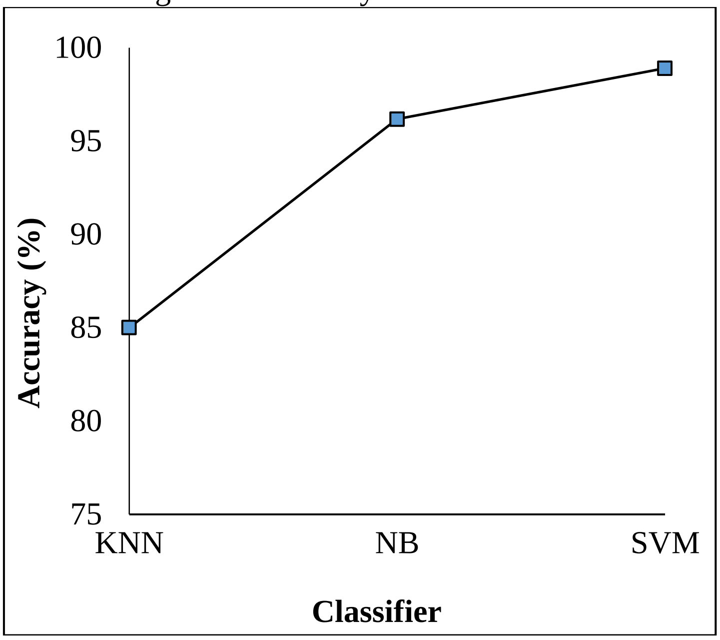

Figure 3: Accuracy in % for video 2

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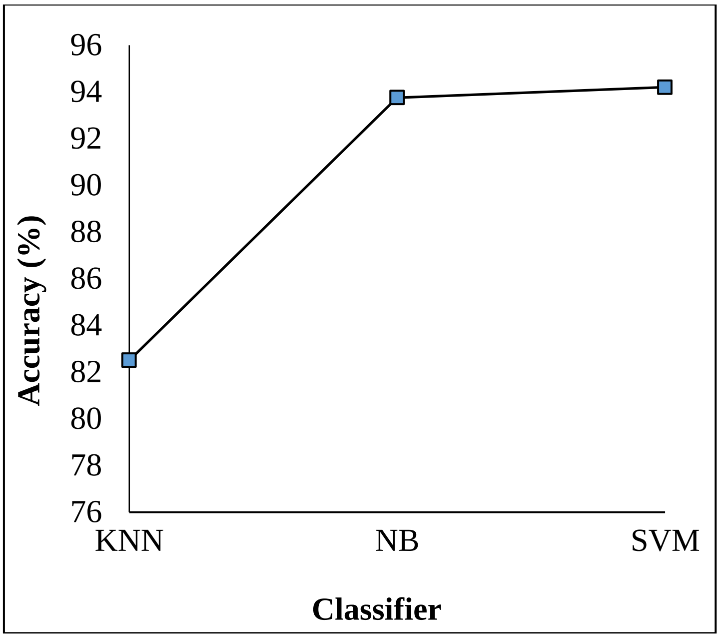

Figure 4: Accuracy in % for video 3

Figure 2 shows the accuracy in % for video 1 and the result shows that the SVM classifiers has increased accuracy than NB and KNN. Figure 3 shows the accuracy in % for video 2 and the result shows that the SVM classifiers has increased accuracy than NB and KNN. Figure 4 shows the accuracy in % for video 3 and the result shows that the SVM classifiers has increased accuracy than NB and KNN.

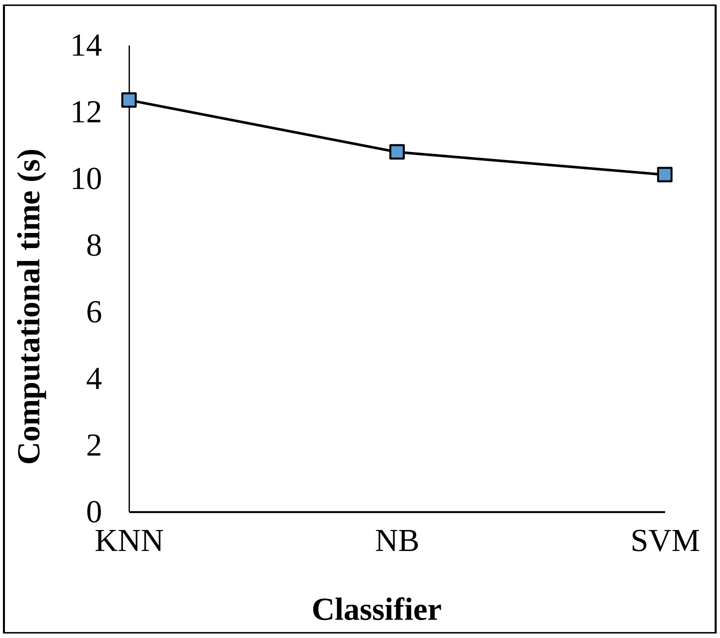

Figure 5: Computational time (s) for video 1

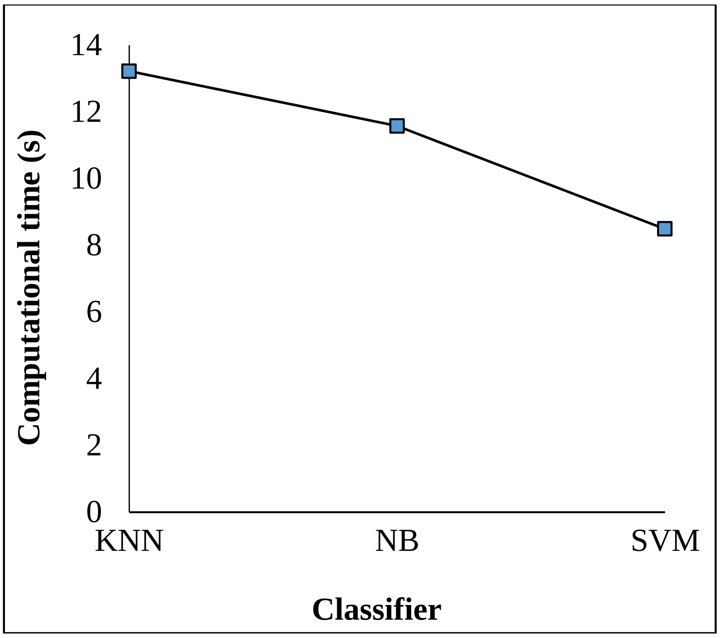

Figure 6: Computational time (s) for video 2

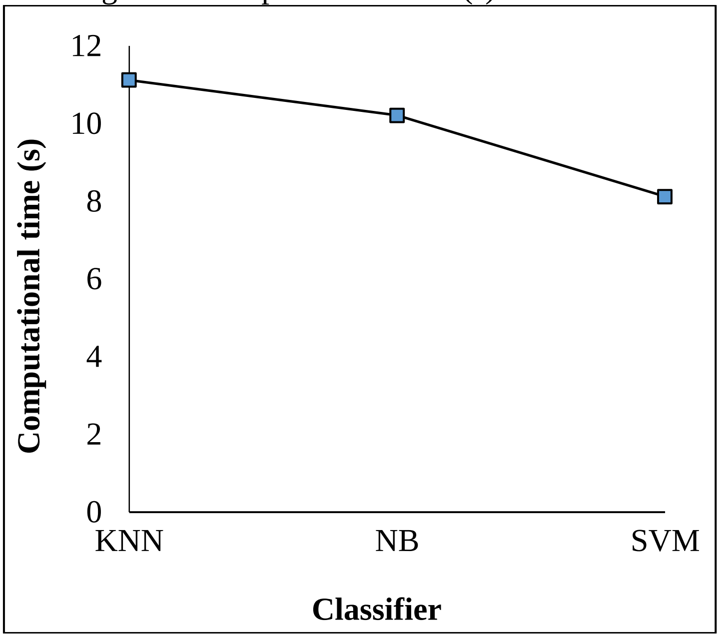

Figure 7: Computational time (s) for video 3

Figure 5 shows the Computational time (s) for video 1 and the result shows that the SVM classifiers has reduced computational time than NB and KNN. Figure 6 shows the Computational time (s) for video 2 and the result shows that the SVM classifiers has reduced computational time than NB and KNN. Figure 7 shows the Computational time (s) for video 3 and the result shows that the SVM classifiers has reduced computational time than NB and KNN.

5. CONCLUSIONS

In this paper, an accuracy of 94.2% is achieved by SVM, while 87.5% accuracy is achieved through NB classification. NB is distinguished by a short time period compared with the other classifiers when looking at the computational time. By comparing various NB and SVM parameters, the results of the SVM classifier are better for the detection of leaf dropping, in terms of computational time and precision.

We plan in the near future to explore more complex models of decay for leaves, including the torn and broken dry leaves into pieces and the putrefaction of wet leaves. Wet leaves can be treated as deformable models so that the design of surrounding objects is held together and deformed. We also work with a knowledge feedback loop on the effect of falling leaves on the environment.

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