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Swift and efficient cinnamon plant disease classification using robust feature extraction and machine learning techniques

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ABSTRACT

The extraction of features and textures holds a crucial significance in the realm of image processing and machine vision systems. Even though artificial intelligence (AI) techniques are superior in attaining the best results in image processing, several challenges remain open for further research in computation complexity, memory, and power requirements. In this context, robust preprocessing techniques are required to address such shortcomings and reduce the computational cost of predictive tasks. This paper employed two feature extraction levels to extract the best possible features from images of the cinnamon plant. Local directional positional pattern (LDPP) extracts global image features, while local triangular coded pattern (LTCP) extracts local features. It helps to provide detailed and more relevant information about the image texture. Once features are extracted, identifying and categorizing diverse textures within an image relies on recognizing their unique features. Typically, descriptors serve as the means for representing images in our work. Afterwards, we used ensemble learning to attain better classification results with the help of weak classifiers. Extracted features are provided to machine learning (ML) models like support vector machines (SVM), random forest (RF), and k-nearest neighbors (KNN) for better classification of the cinnamon category.

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1. INTRODUCTION

A valuable spice with several culinary and therapeutic applications, cinnamon is vital to the world economy. The Food and Agriculture Organization of the United Nations (FAO) reports that 2.23 million tons of cinnamon were produced globally in 2021 and 2022, underscoring the significance of this crop for agriculture. Asia's top producers are Vietnam, Indonesia, China, and Sri Lanka. Maintaining regular, high-quality harvests is dependent on plant health, especially for economically significant commodities like cinnamon. In order to improve output and quality, we examined two prevalent diseases that harm cinnamon's stems and branches: rough bark and stripe canker. Rough bark disease causes uneven, rough patches to form on cinnamon plants, disrupting the bark's smooth texture and detracting from its overall appeal. Fungi in humid environments are the main cause of the illness, which results in structural damage, decreased production, and lower-quality spices. Bacterial infections called stripe canker develop longitudinal sores on the bark that harm tissue, slow growth, and reduce the amount of cinnamon produced. These illnesses can negatively affect agriculture, and diagnostic diagnosis by hand is a long process. Thus, it is essential to integrate cutting-edge technology such as deep learning (DL) and machine learning (ML) for rapid, automated illness identification.

Indeed, feature and texture extraction play a vital role in image processing, particularly within a machine vision system [1]. Machine and DL might be superior in handling images and feature extraction because of its automatic learning characteristics [2], [3]. However, memory requirement, computation complexity, and power are still challenges [4]. While training the model, algorithms may take millions of features from the image as input. Some of the features are relevant and some of the features are not relevant. It leads to inaccurate results. It also increases computation complexity [5]. To address the above issues, we needed robust preprocessing, segmentation, and feature extraction techniques [6]. Many researchers are given numerous solutions for efficient feature extraction/image representation. Some of the works are discussed as follows. In general, color, slope, size, intensity, and slope are utilized for representing images [7]. Texture information are low level features which are normally used to identify the objects in an image. We may have diverse textures in an image, it could be identified and categorized because of its unique features. In general descriptors are used for image representation. It is majorly classified into two namely, global, and local descriptors [8]. Global descriptors take the whole image as an input for its representation. Local descriptors mainly concentrate on extracting relevant information from the image. Numerous descriptors are proposed for effective feature extraction/pattern recognition like local binary pattern (LBP) [9], scale invariant feature transform (SIFT) [10], speeded-up robust features (SURF) [11], and histogram of gradients (HOG) [12].

Local binary descriptor is one of the well-known techniques for image representation [13]. It uses neighborhood details of the pixels for its representation. Research by Pietikäinen [14] the authors proposed the very first binary descriptor called LBP. It works based on the local contrast of an image. It takes every pixel intensity for its representation. It results in increased computational complexity. To address the above, local directional positional pattern (LDPP) and local triangular coded pattern (LTCP) [15], [16] are proposed by taking computation complexity as a major consideration. In the proposed approach, we used two levels of feature extraction for extracting best possible global and local features. LDPP is used for extracting global features of an image. LTCP is used for extracting local features from the level 1 extracted. It gives improved object recognition rate. Finally, we trained the model using extracted features. This contributes to an enhanced level of accuracy while simultaneously mitigating computational complexity.

2. RELATED WORK

Plant disease detection from photos has showed potential for DL, and wide residual networks (WRN) in particular. According to Li *et al.* [17] although this approach has shown efficacy on generic plant leaf datasets, it has not yet been applied to diseases of the cinnamon bark, which is an important subject for future research. More sophisticated DL models for agricultural disease identification have been created in recent studies. A hybrid AlexNet-inception-V4 model improved disease detection by achieving high accuracy across a range of crops [18]. Furthermore, Guo *et al.* [19] convolutional swim transformer (CST) showed remarkable resilience under many circumstances. Nevertheless, more optimization is necessary because to the CST's massive size and processing requirements.

According to Chhetri *et al.* [20] DL algorithms that use domain knowledge can greatly improve the categorization of plant diseases. DL and structured knowledge representation were integrated in a recent study to increase simplicity and accuracy, particularly with noisy data. This strategy presents a viable route for artificial intelligence (AI)-powered agricultural solutions. Ahmad *et al.* [21] a simplified CNN model has been created for effective plant disease identification on devices with limited resources. Through class imbalance correction and memory optimization, this method allows for quick model setup and training. The model shows good accuracy on difficult datasets, which qualifies it for real-world use.

Research by Rajeena *et al.* [22] outperforming current methods, a novel model utilizing efficient net diagnoses corn illnesses with 98.85% accuracy. This demonstrates how DL has the potential to improve sustainability and lower crop losses in contemporary agriculture. The coffee industry faces challenges from leaf diseases, as discussed by [23]. With potential applications for other crops and illnesses, the research provides an EfficientNetB0 model for reliable detection of Arabica coffee plant diseases. This model offers a compromise between accuracy and computing economy. Research by Rao *et al.* [24] addresses the need for accurate and fast disease detection in apple crops. The proposed scheme combines intelligent segmentation and classification models, leveraging optimization techniques and feature extraction methods. By achieving an accuracy of 84%, this work offers a promising solution to improve the apple industry's health while highlighting the potential for future expansion and development in plant disease classification.

The main objective of this paper is to increase classification accuracy with reduced computational complexity by improving the object recognition rate using lightweight algorithms instead of DL architectures. LDPP is used for global feature extraction, taking the whole image as input, and LTCP is used for local feature extraction, taking extracted features as input. Some of the techniques and algorithms we have used for improving object recognition rate in the paper are discussed as follows.

2.1. Local directional position pattern

Vasudha and Kakkar [15] proposed a descriptor LDPP for image representation. In LDPP, 8 bits binary code is used to represent every pixels. At the outset, 3*3 image matrix is categorized into south, south west, south east, north, north east, and north west. For code generation, it uses strength positions and its directions. Krish mask is used for calculating strength of the pixels. To generate the 8-bit code for a pixel, highest and second highest strength values are considered. Binary values are generated from their positions based on the equation [1]. It generates different patterns for different edges.

$$LDPP(x) = \sum_{i=0}^{7} l_i X 2^i$$

$$\mathrm{G}L = A \; OR \; K \quad (1)$$

Where $\mathrm{A} = \mathrm{B(G)OR\ binary\ } \big(\mathrm{argD(G)}\big)$

$K = B(G)OR\ binary\ \big(argD(E)\big)$

$G \in (R_0, R_1, \dots \dots \dots \dots \dots R_7)$

$E \in (R_0, R_1, \dots \dots \dots \dots \dots R_7)$

2.2. Local triangular coded pattern

Arya and Vimina [16] proposed a descriptor LTCP for image representation. LTCP is one of the low computational descriptors. They used 8-bit code for representing pixels. In general, intensities of pairs of pixels are utilized for pixel representation. It results in increased computational complexity. To address the above, the authors proposed LTCP [12].

2.3. Steps involved in local triangular coded pattern

At the outset, the 3*3 image matrix is divided into four regions namely east, west, north, and south. For representing each pixel, triangular pattern is generated in all the directions with respect to center pixel located in (0,0). Various codes are generated by rotating the pixels by 90° and 180°.

For generating the code, pixel intensities are compared with the threshold level. Intensity level of the centre pixel is taken as threshold value. If the intensity level of the neighborhood pixel in the tri angular region is greater than the threshold then the code is 1, else it is 0. It is represented as (2):

$$CP_i = \sum_{i=0}^{n} b\,(P_i - C) \geq (n+1)/2$$

$$LTCP(xc, yc) = \sum_{n=0}^{7} T\,(CP_i - C)2^n \quad (2)$$

$$where, T(v) = \begin{cases} 1, if\ v \geq 0 \\ 0, otherwise \end{cases}$$

where C is the center pixel, Pi is pixel chosen for triangular pattern. V is the difference level in intensities. We used LTCP for extracting the local features from the image which extracted at level 1.

Once the features are extracted, it is fed into the data analysis module for its classification. We have chosen support vector machines (SVM), k-nearest neighbors (KNN), and random forest (RF) as bag of algorithms. We trained the model using extracted features it results in better accuracy with less computational complexity.

3. PROPOSED SYSTEM

To reduce the computational complexity associated with the use of higher end algorithms, we proposed a low complexity classification system. The proposed system majorly focused on data acquisition, pre-processing, dimensionality reduction, and classification as illustrated in Figure 1. In this paper, we reduced computational complexity through effective feature extraction and achieved improved accuracy using weak classifiers such as SVM, KNN, and RF instead of employing strong classifiers or deep neural network architectures. For experimentation, we used cinnamon plant disease dataset. The modules involved in the proposed system are discussed as follows.

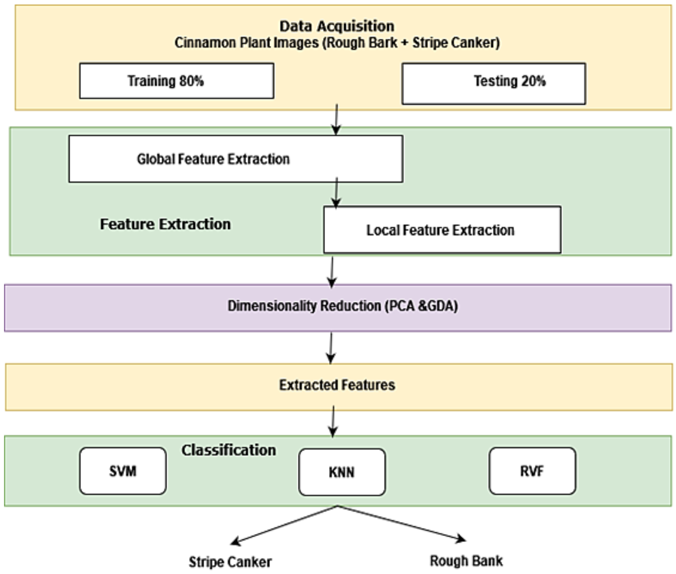

Figure 1. Architecture of the proposed system

3.1. Data acquisition

For experimentation, we used cinnamon dataset collected from Kaggle. It encompasses two image categories: one depicting a cinnamon plant with a rough bark as shown in Figure 2 and the other featuring stripe canker as shown in Figure 3. The dataset comprises a total of 528 images, with 228 images featuring rough bark and 300 images depicting stripe canker.

Figure 2. Cinnamon plant with rough bark

Figure 3. Cinnamon plant with stripe canker

3.2. Pre-processing module

The focus is on feature/texture extraction and dimensionality reduction. Initially, images are converted from RGB to grey scale. After grey scale conversion, we applied feature extraction techniques to get the best possible features. In this paper, we implemented two levels of feature extraction integrating the features of LDPP [15], LTCP [16] for enhanced and detailed feature extraction. At the first level, LDPP is used for extracting global features of an image, At the second level of feature extraction, the extracted features are fed into LTCP. It provides detailed and minute information about the extracted features, exemplified in Figures 4 and 5.

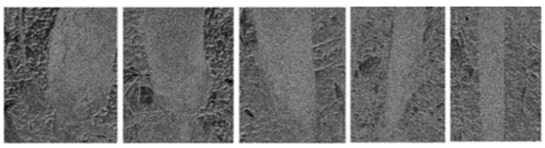

Figure 4. Extracted features using LDPP and LTCP

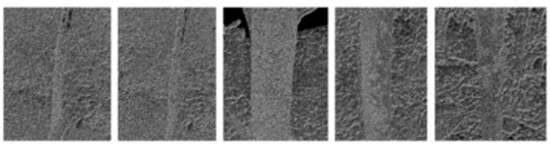

Figure 5. Extracted features using LDPP and LTCP

Once the features are extracted, principal component analysis (PCA) and gaussian discriminant analysis (GDA) [25], [26] are applied over the features to reduce dimensionality and to get enhanced view of the texture. PCA stands out as a widely recognized statistical method for reducing the dimensionality of images. This is accomplished by efficiently mapping from a higher-dimensional space to a lower-dimensional space. GDA helps to control non-linear features for getting more accurate/ correlated features. It results in an increased object recognition rate [14].

3.3. Data analysis

The extracted features are utilized as input for the data analysis module. In this paper, we aimed to achieve strong classifier results by leveraging weak classifiers and improving the object recognition rate. We employed SVM, RF, and KNN as a set of algorithms for classification. The results indicate that the combination of feature extraction with RF yields better results than the other models experimented with. In this approach, we used binary classification; outputs are labeled as rough bark and stripe canker.

4. EXPERIMENTAL RESULTS

The main objective of this paper is to attain better classification accuracy with reduced computational complexity through effective pre-processing techniques. As part of pre-processing, we used LDPP and LTCP for improved object detection. For detailed analysis, we applied various combinations of binary descriptors with varying number of images as 100, 200, 300, 400, and 500 for better object recognition, as shown in Figure 6. The results indicate that the object detection rate improved when we applied the combination of LDPP and LTCP.

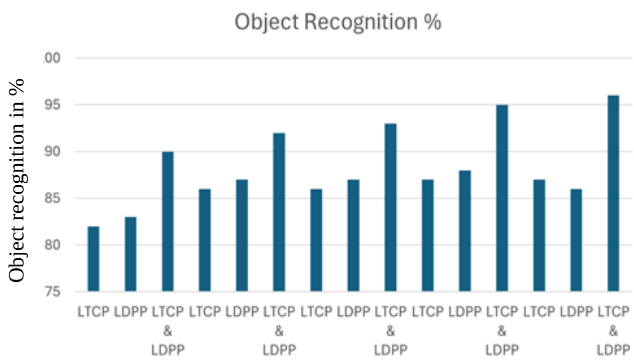

Figure 6. Object detection % of different descriptors by varying number of images as 100, 200, 300, 400, and 500

Detailed experimentation was conducted over various models and their combinations, as shown in Table 1. Initially, we trained the models using the original dataset without feature extraction. After that, we trained the models with the feature-extracted dataset using LDPP, LTCP, and LDPP with LTCP. In the first case, raw datasets without feature extraction are used. In the second case, features are extracted using LDPP. In the third case, features are extracted using LTCP. In the final case, we used two levels of feature extraction: LDPP for extracting global features and LTCP for local feature extraction. The experimental results indicate that RF with LDPP and LTCP achieved higher accuracy compared to other models, as shown in Figure 7. We also measured the computational complexity for all the cases. The experimental results show that the combination of LDPP and LTCP with RF provided good accuracy with reduced computational complexity. Computational complexity is measured by varying the number of pixels, as shown in the Figures 8(a)-(f).

Table 1. Classification accuracy of the proposed system

	Classification accuracy in %		
Feature extraction	SVM	KNN	RF
Without feature extraction	78.21	82.56	81.26
With LDPP	79.12	83.13	85.17
With LTCP	80.78	85.7	87.2
With LDPP and LTCP	81.78	89.7	93.5

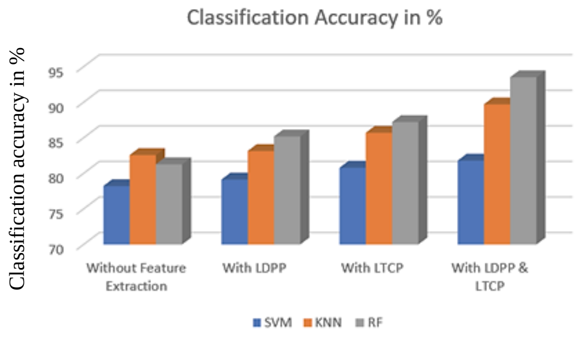

Figure 7. Experimental results of the proposed system

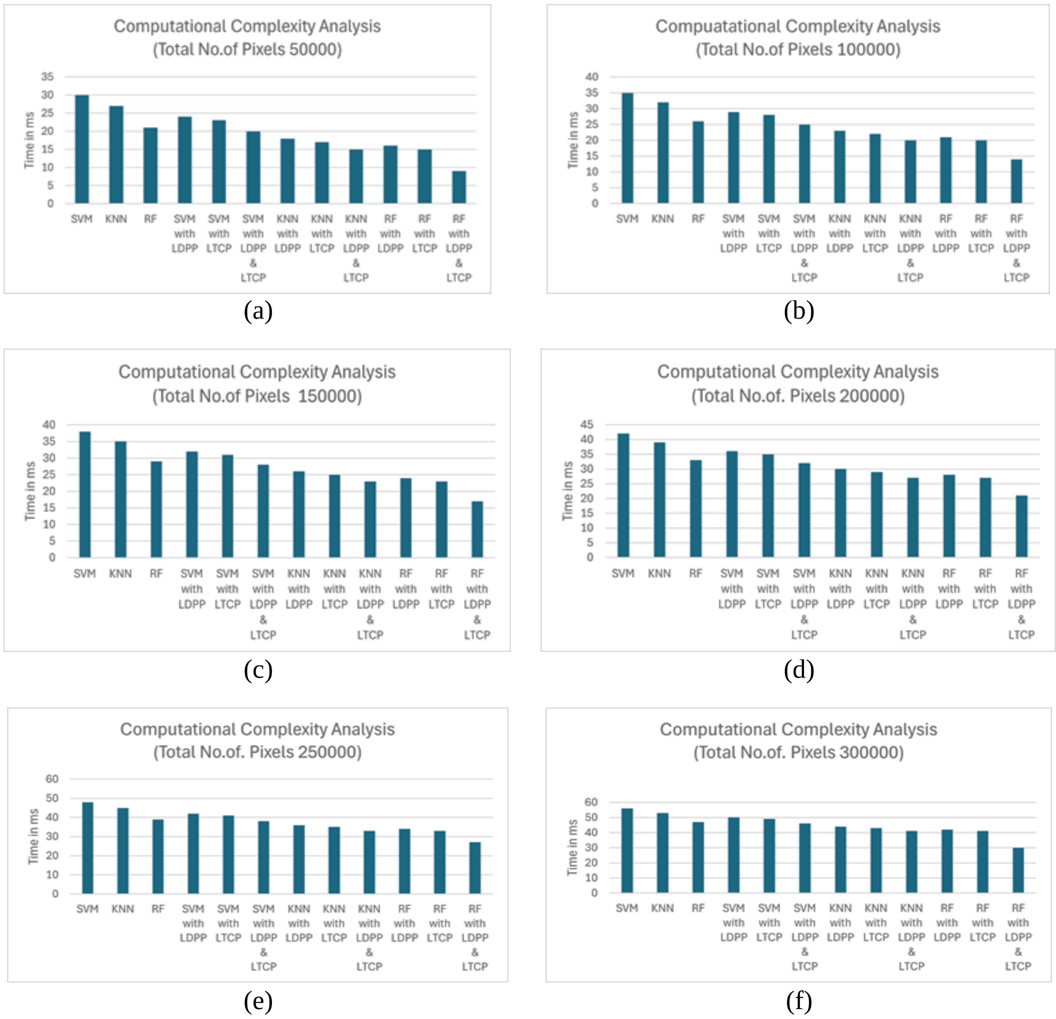

Figure 8. Computational complexity analysis over; (a) 50,000 pixels, (b) 100,000 pixels, (c) 150,000 pixels, (d) 200,000 pixels, (e) 250,000 pixels, and (f) 300,000 pixels

5. CONCLUSION

In this paper, we proposed a low complexity classification system to reduce computation complexity demands while using higher end algorithms. By focusing on feature extraction and dimentionality reduction, we achieved increased classification accuracy using weak classifiers such as SVM, KNN, and RF instead of resource intensive deep neural network architectures. Our approach involved converting images to grayscale, followed by two levels of feature extraction using LDPP and LTCP. This method allowed us to capture both global and detailed features effectively. PCA and GDA were then applied to further reduce dimensionality and enhance the extracted features. The experimental results proven that combining LDPP and LTCP with the RF classifier attained increased accuracy, achieving a significant improvement over other models experimented. Through rigorous experimentation, we demonstrated that our proposed system also reduced computational complexity. The combination of LDPP and LTCP with RF achieved an accuracy of 93.5%, outperforming other test cases. Furthermore, our analysis proven that this approach maintained lower computational complexity, making it a practical solution for real-world applications where resources are limited. In conclusion, our proposed low-complexity classification system offers an effective and efficient method for image classification tasks, particularly in applications such as plant disease detection. Future work could explore the application of this system to other datasets and domains, as well as the integration of additional pre-processing and feature extraction techniques to further enhance performance.

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