Pigeon Pea Leaf Disease Classification using BoVW and DSIFT

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ABSTRACT
Plant diseases are continually emerging on leaves, posing a significant threat to agricultural productivity and food security in many parts of the world. Early detection and precise diagnosis of these plant diseases are essential to mitigate financial losses and environmental damage caused by misdiagnosis. In this paper, presented a feature-based approach for detecting pigeonpea leaf diseases from images. The pigeonpea (Cajanus cajan (L.) Millsp.), a member of the Fabaceae family, is a crucial legume shrub found in the semi-arid tropics and subtropics of Asia and Africa. Dense Scale-Invariant Feature Transforms (DSIFT) and Bag of Visual Words (BoVW) features are employed for feature extraction. Classification methods namely, SVM, KNN, RF, DT, XGBoost and Light GBM and CNN are used for disease classification with different combinations of DSIFT and BoVW features. Light GBM and CNN have yielded better accuracy compared to other classifiers.

General Terms
Digital image processing, Machine learning, Deep learning

Keywords
Leaf diseases, DSIFT, BOvW, Classification

1. INTRODUCTION
A staple legume crop grown extensively throughout Asia's and Africa's semi-arid tropics and subtropics, pigeonpea (Cajanus cajan) is essential to both sustainable agriculture and food security [1,2]. It is valued for its high protein content and ability to thrive in harsh, drought-prone environments. The crop is a hardy shrub with compound leaves, typically comprising three leaflets that are green and oval-shaped. Despite its resilience, pigeonpea is vulnerable to various diseases that affect its leaves, including fungal infections like Fusarium wilt and Phytophthora blight, as well as viral diseases such as sterility mosaic disease [3]. These diseases can lead to significant reductions in yield and quality, making effective disease management crucial for maintaining agricultural productivity. Therefore, early detection and precise diagnosis of plant illnesses will not only save a great deal of money on needless planting, but also lessen the financial losses and environmental damage that result from misdiagnosing diseases [4].

Leaf spot disease and sterility mosaic disease are the most prevalent illnesses [7] in pigeonpea leaves. The eriophyid mite vector is the means by which the pigeon pea sterility mosaic virus, which causes sterility mosaic disease (SMD), spreads [4]. Common symptoms of SMD infection in plants include reduced leaves, yellow mosaic, partial or complete sterility, chlorotic patches, and increased vegetative growth [5]. Cercospora species are the cause of leaf spot. One of the fungi that cause pigeon pea illnesses is Cercospora cajani Hennings [6]. The symptoms initially manifest as brown patches that eventually develop dark brown [7]. The most effective method is to use effective image processing tools and a machine learning-based approaches for diagnosing pigeonpea leaf diseases.

In this paper, DSIFT and BOvW feature extraction approaches are presented for detection of sterility mosaic disease and leaf spot disease on pigeon pea leaves. DSIFT uses photos to extract robust and detailed local characteristics. BoVW makes picture classification and other visual recognition tasks easier. BoVW's capacity to transform complex feature data into a digestible and efficient representation for classification tasks is enhanced by DSIFT's resilience to scale, rotation, and noise. When combined, these local elements into a global representation, they improve image recognition's performance and accuracy. The classification of the disease is done using Decision tree (DT), Random Forest (RF), KNN, SVM, Gradient Boosting model (GBM), XGBoost and CNN classifiers.

The remaining of the paper's organization is as follows. Section 2 examines the relevant literature. Suggested approach for pigeon pea disease detection are introduced in Section 3. The implementation outcome and the key findings of the study are presented in Section 4. Conclusion is presented in Section 5.

2. LITERATURE STUDY
Pigeonpea leaf diseases can significantly reduce crop yields in both quality and quantity, posing a major challenge to agricultural productivity. To improve the accuracy of detecting and classifying leaf diseases, advanced techniques such as image processing, machine learning, and deep learning models are frequently employed. These machine-based learning methods enhance detection capabilities by identifying complex patterns within large datasets, leading to more precise and reliable diagnosis of pigeonpea leaf diseases. A brief review of methods available in the literature is presented below.

A combination of HOG, LBP and PCA is presented by Devi, M.B. et al. [19]. In order to minimize the feature dimensions, PCA was utilized. Naive Bayes, Logistic Regression, Support Vector Machine, Decision Tree, and HistGradientBoosting classifiers are used for classification. The Pepper leaf picture dataset was utilised for experiments in disease identification. The HistGradientBoosting Classifier yielded an accuracy of 89.11%.

A deep learning-based method is presented by Loti et. al. [20]. Features derived from deep learning approach were compared with features collected from chili pests and diseases using a conventional method. A total of 974 pictures of chili leaves were collected, that including two types of pest infestations, five various disease types, and a healthy type. To extract important pest and disease features from the images of chili leaves, six conventional feature-based approaches and six deep-learning feature-based approaches were employed. For the identification challenge, the collected characteristics were fed into three machine learning classifiers, namely, artificial neural network (ANN), a random forest (RF), and a support vector machine (SVM). Using the CNN features and SVM classsifier, the accuracy of 92.10% was attained.

Sunil S. Harakannanavar et. al. [21] presented an approach to enhance the quality of tomato samples. The leaf samples are scaled to 256 × 256 pixels and Histogram Equalization is applied to enhance the image. Contour tracing strategy is used to extract the boundaries of leaf samples. A variety of descriptors, such as Principal Component Analysis, Discrete Wavelet Transform, and Grey Level Co-occurrence Matrix, are used to extract the leaf samples' informative qualities. Machine learning methods, namely, Support Vector Machine (SVM), Convolution Neural Network (CNN), and K-Nearest Neighbor (K-NN) are for classification. CNN yielded better accuracy of 99.6%.

Using visual features extracted from leaf photos using Bag of Visual Words (BoVW) and the Support Vector Machine (SVM) classification approach is presented by R. Dijaya et. al. [22]. The study is carried out to diagnose illnesses of maize plants. The training dataset's corn leaf images' salient features are identified and described using the Speeded up Robust Feature (SURF) technique. To conduct the experiment, the plantvillage public dataset is used. According to the experimental results, the proportion of the strongest key points is 80%, there are 800 clusters, and the classification accuracy is 85%.

Table 1. Summary of state-of-the-art methods for plant leaf disease detection

Reference	**Year of Publication**	**Leaf Dataset**	**Methods used**	**Result (accuracy in %)**
Devi, M.B. et. al. [19]	2021	Pepper	HOG, LBP, PCA applied to get feature representations, then classifiers like Naive Bayes, Logistic Regression, Support Vector Machine, Decision Tree, and HistGradientBoosting used	89.11
Loti et. al. [20]	2021	Chili	Features extracted from CNN and classified by SVM	92.10
Sunil S. Harakannanavar et. al. [21]	2022	Tomato	CNN	99.6
R. Dijaya et. al. [22]	2022	Maize	SURF, BOvW and SVM	85
Pawar, Sagar et.al. [23]	2023	Pigeon pea	VGG16	88
Mehmood, S. et. al. [24]	2023	Cotton	SIFT, SURF, HOG, GLCM, and Gabor wavelets filter employed. Then a SVM classifier was adopted for disorder classification.	92
Sandesh Bhagat et.al. [25]	2024	Pigeon pea	Proposed light weight deep learning model	94.14

Sterility Mosaic Disease (SMD) is a serious obstacle to pigeon pea (Cajanus cajan) agriculture in the Indian subcontinent because it can spread quickly and lead to epidemics. A study on the pigeon pea crop is presented by Pawar, S. Y. et al. [23]. CNN architecture is pretrained using the classification-focused VGG16 architecture. The findings indicated that the average accuracy for identifying SMD in pigeon pea harvests is 88%.

A study on cotton leaf diseases, including Angular Leaf Spot, Bacterial Blight, Cotton Curl Leaf Disorder (CLCuD), and Alternaria Disease, is conducted by Mehmood, S. et al. [24]. Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), Gray-Level Co-occurrence Matrix (GLCM), and Gabor wavelets filter were the feature extraction methods employed in this work. To classify disorders, a Support Vector Machine (SVM) classifier was trained. The Gabor Wavelet Filter Feature Extractor performed better, obtaining 92% accuracy.

Multi-kernel depthwise separable convolutions were introduced by S. Bhagat et al. [25]. The accuracy of experiments conducted on the pigeon pea dataset is 94.14%.

Summary of state-of-art methods is presented in Table 1. The literature survey makes clear that while many researchers have examined leaf disease detection, more research has been done on the leaves of tomato, cotton, pepper, chili and maize plants than on the leaves of pigeon pea plants.

In recent days deep learning model is widely employing for image categorization to get accurate result. However, machine learning based classifying strategies also yield better results result if good feature selection technique is used. In this paper, a unique feature-based method for pigeon pea leaf disease identification is proposed.

3. PHASES OF PIGEON PEA LEAF DISEASE IDENTIFICATION

The proposed system of pigeon pea leaf disease identification consists of phases, namely, pre-processing, feature extraction, classifier as illustrated in Fig. 1.

Proposed algorithm:
Input: A pigeon pea image database, windows size w, step size s and k for K-mean cluster.
Output: Performance metrics (accuracy, precision, recall, F1-score, evaluation time) and the trained classifier model.

Step 1: Gather pictures of the leaves on pigeonpea plants.
Step 2: Prepare the photos by resizing them to a standard size and cropping them to a square shape. Then, use the CLAHlet RetiGaussian Filter to enhance the quality of the image.
Step 3: For each image, extract DSIFT features using a fixed step size S. Gather all DSIFT descriptors from all leaf images.
Step 4: Utilizing the K-means clustering technique, form 128 groups. To create a 128-dimensional feature vector for each descriptor, calculate the mean of each cluster.
Step 6: For each image, assign DSIFT descriptors to nearest visual word by employing BOvW.
Step 7: Construct a histogram of visual word occurrences for each image.
Step 8: To create the classifier model, train the system with BoVW histograms.
Step 9: Evaluate the trained classifier model's ability to predict both healthy and diseased pigeon pea leaves.
Step 10: Analyze the model's performance in terms of recall, accuracy, precision, and f1-score.

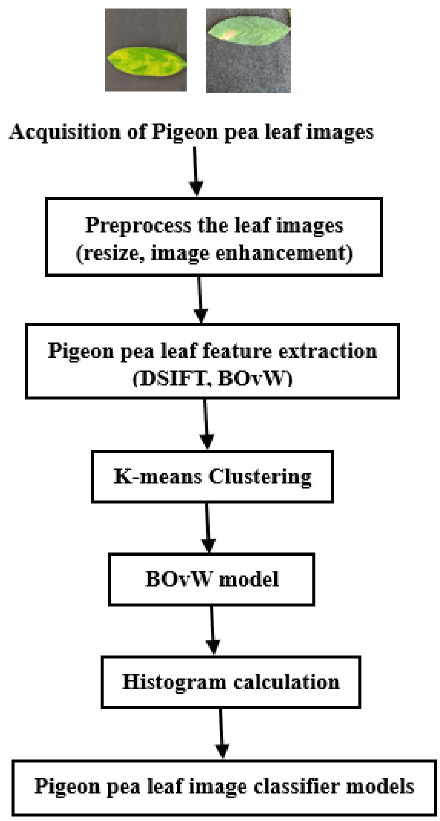

Fig. 1. Block diagram of proposed approach

3.1 Pigeon pea leaf image collection

For the purpose of collecting the plant leaves, the pigeon pea field at the Agriculture Research Station, Hittinahalli Campus, Vijayapur (Lat 16.769281 and Long 75.748891), Karnataka, was chosen. Using a smartphone fitted with an Oppo F19 pro 48 MP camera and a Sony Cyber-Shot DSCW810 20.1 MP digital camera, images of pigeon pea leaves were taken in natural environments, at various angles, against both a uniform and non-uniform background. The collection contains pictures of leaf spot and sterilic mosaic, two frequent diseases that pigeon pea plants contract, in addition to pictures of healthy plants. Table 2 provides information about the image dataset, and Fig. 2 displays some sample photos. The classification and labelling of all gathered data were done so by agricultural specialists. For further research pigeonpea leaf dataset version 1 made online available [16].

Table 2. Dataset details

Leaf type	Count
Healthy	300
Leaf spot	300
Sterilic mosaic	300
Total	900

(a) (b) (c)

Fig. 2. Sample photos of pigeon pea leaf (a) sterilic mosaic (b) leaf spot (c) healthy are shown.

3.2 Pre-processing of pigeon pea leaf images

To standardize the photos, they were cropped to 256 by 256 pixels. This 900-image dataset consists of a test set (30%, or 270 shots) and a training set (70%, or 630 images). There are 300 photos in each of the three classes: leaf spot, sterility mosaic, and healthy. The accuracy of pigeon pea disease detection is limited by low light and noise, and obtaining high-quality monitoring photographs is more challenging (Fig. 3a). In order to prevent this, the study enhances image quality (Fig. 3b) using an efficient CLAHlet RetiGaussian Filter [8].

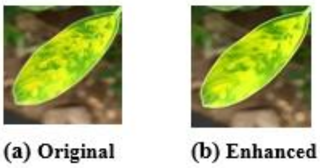

Fig. 3. Prior to and following preprocessing to improve picture outcomes.

3.3 Dense Scale-invariant feature transform (DSIFT)

The SIFT technique was introduced by Lowe [10] as a means of extracting local features from images while maintaining invariance to affine transformations, scaling, and rotation of the images. As a result, it is believed that the SIFT technique is the most reliable local invariant feature descriptor for image processing [9,11]. Unfortunately, significant computation requirements result in low image processing performance for the SIFT technique, which includes feature identification and description stages. Consequently, the dense scale-invariant feature transform (DSIFT) algorithm [12,13], an enhancement of the original approach, has been created and put to use. Based on a predetermined step length *s*, the DSIFT method applies a fixed-size rectangular window *w*, for sampling, moving from the top to the bottom and from the left to the right of the image. The window center serves as the focal point, and a 16-pixel-wide picture block surrounding it is segmented into 4 × 4 pixel-sized cells. The SIFT technique is used to produce a gradient histogram in eight orientations. This results in a feature vector with (4 x 4 × 8) = 128 dimensions, which forms the DSIFT descriptor.

3.4 Bag of visual words (BOvW)

The BOVW model, which was proposed by Sivic and Zisserman [14], is frequently employed in machine vision applications [15,22]. The conventional BOVW model consists of four main phases. Feature extraction and description is the initial phase. The dense SIFT descriptors in this study, which consisted of a 128-dimensional vector, are represented by the DSIFT output, which shows the local invariant feature spots for each image. Using a K-means algorithm to parse the dense SIFT descriptors, a visual vocabulary is created in the second stage. You might think of each cluster center as a dictionary's visual word. As a result, every visual word constitutes a visual vocabulary, whose size is determined by the total number of words. The third step is to analyze the number of visual word occurrences in each image, wherein the image can be represented as a numerical vector histogram. The final step is feeding this vector to classifier model.

3.5 Classification techniques

Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), Decision tree (DT), Gradient Boosting Model (GBM), XGBoost are employed for the illness classification of pigeon pea leaf images. All of these machine learning methods has advantages and can help classify image samples in a reliable and precise manner.

3.6 Evaluation metrices

The performance of the proposed method is evaluated using an assessment measure, including accuracy, recall, precision, and F1-measure metrics [17].

1) Accuracy: is calculated by dividing the percentage of successfully identified photos using the following formula.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

2) Precision: The precision of the algorithm indicates how reliable its positive predictions are, up to a specific point. Stated in another way, it is the ratio of genuine positives to both true and false positives when determining the positivity of the forecasts.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

3) Recall: Also known as sensitivity or true positive rate, recall quantifies an algorithm's ability to identify every positive case. It assesses suitably identified positive instances. It considers deceptive negative values in addition to true positive values.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

4) F1 Score: It is calculated by taking the harmonic mean of the recall and precision values. The F1score value goes from 0 to 1. Prediction scores close to 1 indicate that the model is operating exceptionally well.

$$F1\,Score = 2X\frac{(Precision * Recall)}{(Precision + Recall)} \quad (4)$$

4. EXPERIMENTAL RESULTS

Python, a language renowned for its simplicity and ease of use, is used to implement the proposed approach. Google Colab is used for the implementation, offering a cloud-based, collaborative platform that facilitates effective development and execution. This section looks at the performance of various classification strategies.

Table 3. Performance of analysis of different classifiers

Classifier	Accuracy	Precision	Recall	F1 Score
SVM	0.85	0.85	0.86	0.85
KNN	0.81	0.83	0.81	0.81
RF	0.86	0.85	0.87	0.85
DT	0.78	0.79	0.78	0.78
XGBoost	0.86	0.85	0.86	0.85
Light GBM	0.87	0.87	0.87	0.87
CNN	0.90	0.89	0.89	0.88

Features computed by a dense SIFT are combined into visual vocabulary i.e. global representation by employing BOvW. This fused feature vector is then fed into machine learning classifiers namely SVM, KNN, Random Forest, XGboost and LightGBM and convolution neural network. CNN explores the potential of both traditional feature extraction and modern deep learning. Compared to machine learning classifiers, CNN classification technique provided better results in terms of accuracy. Table III gives the detailed performance analyses of in terms of accuracy, precision, recall andF1-score on different classifiers like SVM, KNN, Random Forest, XGboost, LightGBM, and CNN respectively. Figure 4 shows graphical depiction of performance of the classifiers. The proposed method is compared with the most advanced methods in Table 4.

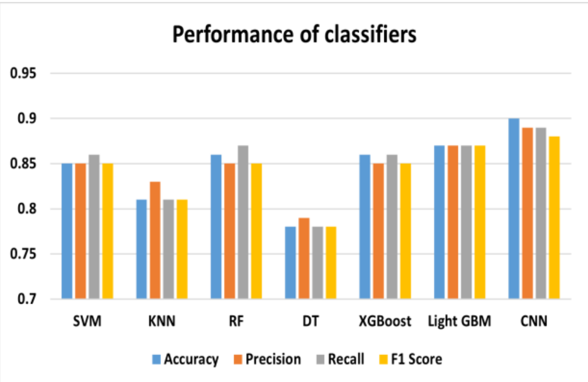

Figure 4 Graphical representation of performance of the classifiers

Table 4 Comparison of state-of-the-art methods

Si. No.	Reference	Method	Dataset	Result (accuracy in %)
1	R. Dijaya et. al. [22]	Corn	SURF +BOvW feature vector and SVM applied	85
2	Panigrahi, K.P [18]	Maize	Shape, color, texture features and random forest used.	79.23
3	Devi, M.B. et. al. [19]	Pepper	HOG, LBP, PCA applied to get feature representations, then classifiers like Naive Bayes, Logistic Regression, Support Vector Machine, Decision Tree, and HistGradientBoosting used.	89.11
4	Pawar, Sagar et.al. [23]	Pigeon pea	VGG16	88
5	Proposed	Pigeon pea	DSIFT + BOvW + CNN	90

5. CONCLUSION

Agriculture might be greatly enhanced by automated crop disease identification, which would have an impact on both food security and long-term economic viability. New and creative approaches to identifying and controlling agricultural diseases are provided by technologies like machine learning and image recognition systems. In this paper a fusion of features using highly effective dense SIFT, BOvW attribute vector fed into CNN model, for the automated identification and categorization of significant pigeon pea leaf diseases. The suggested models achieved a remarkable 90% accuracy thereby highlighting its effectiveness in identifying pigeonpea leaf diseases. Enhancing the present accuracy score is feasible by incorporating deep learning models. Future research will concentrate on deep learning techniques and real-time implementation.

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