Multimedia Tools and Applications (2024) 83:39117–39134
https://doi.org/10.1007/s11042-023-17172-1

Performance enhancement of kernelized SVM with deep learning features for tea leaf disease prediction

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Received: 15 October 2022 / Revised: 17 August 2023 / Accepted: 19 September 2023 /
Published online: 7 October 2023

Abstract

India is one of the world's leading tea producers, yet more than 70% of the country's tea is consumed domestically. Tea leaf diseases have a significant impact on the quality and yield of tea. So, it is very important to find a more accurate method to identify tea leaf diseases correctly. Due to very limited number of tea leaf images, classification is very difficult. Very frequently overfitting of model occurs. To cope up with this, we applied images augmentation process, that increased dataset nearly fourteen times. But still this number of datasets is not adequate for DL based classification. So, we used here deep learning for feature extraction and machine learning based classifier for classification. In this work, we have proposed a hybrid technique that combines deep learning-based features of augmented dataset with machine learning based classifier for getting better classification result. In proposed work, VGG-16 is used for colour feature extraction from the tea leaf dataset. Based on this feature, model is built and several machine learning-based classifiers like KNN, XGB, Random Forest, and kernelized SVM are employed for classification task. Our proposed model achieved highest classification accuracy with Sigmoid and Linear kernel based SVM and VGG-16 features. The accuracy of proposed model is 96.67%. We compared our proposed work with existing work on tea leaf dataset and found that our model is performing comparatively better.

Keywords Classification · VGG-16 · Augmentation · KNN · RF · XGB · Kernel SVM

1 Introduction

The tree or shrub Camellia sinensis is a member of the family Theaceae. The leaves that are picked for this purpose are used to make tea, which is a fragrant drink. This plant has elliptical leaves with a leathery texture and a border with sharp edges. The leaves are a matte green colour. Because of how they are grown and trimmed, tea plants rarely reach their full potential as bowl-shaped trees. Tea plants that are meant to be used for making tea don't have flowers. When tea plants are allowed to flower, they make single or small

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clusters of fragrant white flowers. Tea trees can grow up to 15 m (49 feet) tall and live for 30 to 50 years in the wild [1, 2]. India is one of the world's leading tea producers, yet more than 70% of the country's tea is consumed domestically. Other notable teas that originate in India are Assam and Darjeeling. The Indian tea business has developed to be one of the most technologically advanced in the world, owning numerous global tea brands. The Tea Board of India oversees all aspects of the Indian tea trade, including production, certification, and export. History of tea in India [3]. Currently, as for a long time in the past, India is the leading tea producer in the world. Tetley and Typhoo, two well-known British tea brands, were acquired by Indian tea firms. 103 million kg of tea were produced by Camellia PLC, the parent firm of Goodricke Group, an Indian tea behemoth [4]. As of 2013, green tea consumption in India had increased by more than 50% every year [5].

As a major producer and consumer of tea, China plays an essential role in global trade. With a production of 2.41 million tonnes of tea and a market value of 170.2-billion-yuan, China's tea industry had a significant impact on the national economy in 2016. There are roughly 130 different types of illnesses that affect tea leaves in China, and these diseases have a negative impact on the health of tea plants and the quality of the tea they produce. Aside from that, sick leaves lower the quality of tea, which costs tea growers a lot of money. Tea leaf diseases may be identified precisely, and preventative actions can be taken in time to reduce tea output losses, improve tea quality, and increase the profitability of tea producers. Tea leaf infections are currently identified primarily by on-the-spot investigations and experience-based judgments by plant protection experts. Aside from the difficulty of getting to the steep hillsides where tea is cultivated, it is also expensive to use artificial disease identification methods. The use of machine learning and image processing technologies for plant disease identification is now commonplace [6]. Agriculture problems need to be solved with cutting-edge techniques so that there is enough food. In this situation, agricultural businesses pay a lot of attention to AI-based methods. ML has been used in agriculture for a wide range of tasks using several common methods. Also, the study of agriculture has come a long way thanks to deep learning (DL). This is because deep learning algorithms are built to automatically pull-out features. Correctly classifying plant diseases is very important if you want to improve crop yields and quality while using less agrochemicals like fungicides and herbicides. So, automation in agriculture is a growing field of study. Due to how often diseases that affect plants are found in similar places, this farming task is harder than it may seem at first. In light of this, a number of studies have been done to find better ways to group plant diseases [7]. ML models have been used a lot to look into how to classify plant diseases [8]. In the same way, hyperspectral [9] and multispectral [10] imaging has been used to find plant and leaf diseases. But since the invention of deep learning (DL), cutting-edge architectures have shown promise for putting plant diseases into groups. Some of these are AlexNet [11], Visual Geometry Group (VGG) [12], DenseNet [13], Inception-v4 [13], and ResNet [11]. In this way, different studies have shown that deep learning-based methods are better than traditional ML approaches. GoogLeNet, a popular DL model, has been shown to be better at classifying diseases in tomato leaves than other ML algorithms, such as SVM and RF models [14]. A support vector machine was used by Hossain et al. in Bangladesh to identify two of the most common tea leaf illnesses, brown blight disease and algal leaf disease (Hossain et al., 2018). The extraction of plant disease traits is essential when using these conventional machine learning approaches like random forest, adaboost, decision trees, and support vector machine to identify plant diseases. Traditional machine learning approaches have difficulty distinguishing between infected and healthy tea leaves because the colour and texture of healthy and diseased tea leaves are so similar [15].

For the classification of multi-class groundnut illnesses, Chaudhary and colleagues used a machine learning approach integrating an upgraded random forest with an attribute evaluator and an example filter [16]. In order to identify rice diseases, Lu et al. suggested a method based on deep convolutional neural networks. Conventional machine learning models were not as accurate as this one [17]. Using a fuzzy logic classification technique, Ehsan et al. were able to more accurately distinguish between healthy and diseased strawberry leaves [18]. Semantic minimum optimization (SMO), K-NN, random forest and naive Bayes were among the classifiers evaluated by Tetila and colleagues for the identification of soybean leaf diseases [19]. As part of his research, Ferentinos created a deep learning system for the identification and diagnosis of plant diseases. Images of healthy and damaged leaves from an accessible database were used as training examples [20]. To classify tomato crop illnesses, Rangarajan et al. used an AlexNet and VGG16 network architecture based on deep learning. A total of 13,262 photos were used for training purposes [21]. It is no longer necessary to manually extract target features for target identification using the deep learning technology that has been developed recently. The identification accuracy of deep learning is high if enough training examples are available. For the detection of maize leaf diseases, Zhang et al. presented deep learning-based improvements to the GoogLeNet and Cifar10 models. Nine different types of maize leaf photos were tested with these two enhanced models [22].

There is a lot of work involved in training the deep learning models above. There are just a few tea leaf's disease testing sites because of a lack of data. In order to use tea leaves as training samples, it is difficult and expensive to collect enough disease data from them. Insufficient tea leaf disease training samples make it difficult to use the deep learning algorithms above to accurately identify diseased tea leaves. So, in this paper we have used VGG-16, a deep learning model for feature extraction for tea leaves and machine learning based traditional classifier such as KNN, SVM, Random Forest etc. to achieve more accurate results than the existing work.

1.1 Research objective

Even though India is one of the world's largest tea growers, it's domestic market takes up more than 70 percent of the country's total tea consumption. Diseases affecting tea leaves significantly reduce both quality and production. The aforementioned deep learning models require a substantial amount of training data in order to be trained. There aren't many places to test for tea leaf's disease because of a lack of funding. In order to train a model, it is difficult and costly to acquire enough data on tea leaf diseases to use as training samples. When there aren't enough diseased tea leaves available for training, it's challenging to achieve high identification accuracy using the aforementioned deep learning methods. Our goal is to create an automated system that can detect diseases in tea leaves with a greater rate of accuracy than existing methods while using a smaller number of training images.

1.2 Contribution

The followings are the key contribution of our present work:

- Developed an automated system that can detect diseases in tea leaves with a greater rate of accuracy than existing methods while using a smaller number of training images.
- Solution of data crisis using augmentation technique.

- Fused deep learning feature with machine learning based classifier to get higher classification results.
- Built hybrid model using VGG-16 features and kernel based SVM classifier. This model outperforms with the existing techniques applied on tea leaves for disease prediction.

1.3 Organization of the paper

The rest of the paper is organized in the following manner. Section 2 discusses related works proposed by a various author, as well as their contributions. The proposed methodology is presented in Section 3. Section 4 presents description of datasets used in this article. Results and discussion of present works is provided in Section 5. The overall explanation of the paper and conclusion of our work is put in Section 6.

2 Related Works

In this section, we have primarily discussed the studies conducted by numerous scientists to identify diseases in tea leaves by various methods. In Bangladesh, brown blight disease and algal leaf disease were identified using a support vector machine by Hossain et al. [15], 2018. Conventional machine learning algorithms, such as random forest, adaboost, decision trees, and support vector machine, rely heavily on the extraction of plant disease features in order to correctly diagnose plant diseases. Because healthy and diseased tea leaves look and feel so similar, traditional machine learning algorithms have a hard time telling them apart.

Diseases affecting tea leaves have a major effect on the final product and the harvest. In order to detect and control illnesses in tea leaves in a timely manner, Hu, Gensheng, et al. [6], 2019 describe a low shot learning approach for disease identification. Using color and texture data, support vector machines (SVMs) can identify and isolate individual disease spots in images of tea leaf diseases. Recently shown conditional deep convolutional generative adversarial networks (C-DCGAN) can take segmented images of disease spots and generate fresh training samples that can be fed into the VGG16 deep learning model for disease diagnosis. After training on augmented disease spot images, the VGG16 deep learning model accurately identified diseases in tea leaves with an average identification accuracy of 91%, demonstrating that SVM can segment disease spot images under low shot learning conditions while retaining the edge information well, and that improved C-DCGAN can generate augmented images with the same data distribution as real disease spot images.

Intelligent tea plucking requires correct identification of tea buds and leaves. To learn about tea buds and leaves and pinpoint optimal picking locations, Wang, Tao, et al. [23], 2021 used the region-based convolutional neural network (R-CNN) Mask-RCNN. Images of tea buds and leaves are captured in a challenging setting; the Resnet50 residual network and a feature pyramid network (FPN) are then used to extract these features; finally, a regional proposal network (RPN) is used to perform preliminary classification and preselected box regression training on the feature maps. Second, the RoIAlign technique of regional feature aggregation creates a feature map with a constant size, hence avoiding quantization issues. The previously chosen ROI is shown here as a feature map. The results of this model can be used for both regression and classification. Finally, the optimal picking spots for tea leaves and buds are pinpointed using the output mask image and the positioning algorithm. One hundred pictures of tea tree blossoms and leaves taken in different settings are used for evaluation. As shown by the data, 93.95 percent of the samples were identified accurately, and 92.48 percent of the samples were recalled accurately. The strategy presented in this study for determining where to gather tea is both adaptable and reliable under difficult conditions.

Semantic segmentation of tea geometrid in natural scene pictures using a discriminative pyramid (DP) network-based technique is proposed by Hu, Gensheng et al. [24], 2021. The method uses strategies like inverting, translating, mirroring, and randomly zooming images to mitigate the impact of uneven lighting on segmentation. As part of this effort, a DP network is developed to improve segmentation accuracy even further. Two of the DP network's smaller subnetworks are the pyramid attention network and the border network. Using a pyramid attention network, we may overcome the difficulties posed by tea geometrids with significant shape variations, small sizes, and difficult detection by collecting global context information about targets at varying scales, expanding receptive fields to focus on small targets, and so on. Tea geometrids may be distinguished from tea tree stalks, broken leaves, and other visually similar backgrounds with the use of the border network's extraction and supervision of semantic borders. The suggested method provides a high degree of accuracy for semantic segmentation of tea geometrids in photographs of natural scenes.

Tea leaf disease is to blame for the declining tea quality and production. The diseased leaf segmentation and weight initialization method used in Hu, Gensheng et al.'s [25], 2022 multi-convolutional neural network (CNN) model MergeModel was used to automatically identify tea leaf abnormalities in small samples. Diseased leaf segmentation may help mitigate the impact of distracting backgrounds on identification accuracy. MergeModel was able to extract multiple unique features because it was built with many different CNN modules. MergeModel's object recognition performance vastly outperformed that of a single neural network. Using the weight initialization technique, we encoded the features of diseased leaves into the convolution filter so that the model could prioritize learning these features at an early stage. This study employed the unconditional generation model, termed SinGAN, to augment data by generating new training samples from the original set of sick tea leaf images. White scab, tea leaf blight, red scab, and sooty mould were just some of the frequent tea leaf diseases that were successfully distinguished between using MergeModel. The new technology allowed for a more accurate diagnosis of even minute tea leaf samples than had previously been possible.

Hyperspectral imaging, as proposed in paper [26] by Zhao, Xiaohu, et al., is an effective and non-destructive alternative to the conventional optical detection approach for plant monitoring. Furthermore, it offers great promise for plant phenotyping in the face of pest and disease outbreaks. Previous uses of hyperspectral imaging for disease detection have been limited to a single disease, making it impossible to rule out the possibility of other co-existing diseases or insect infestations. Researchers examined how the tea green leafhopper, anthracnose, and sunburn (a stress akin to illness) affected tea plants in the lab. A multi-stage approach to determining the causes of plant stress was developed using continuous wavelet analysis (CWA) and hyperspectral imaging. Using CWA feature extraction, k-means clustering, and support vector machine methods, we constructed a model using the random forest technique to identify and differentiate between the three stresses that tea plants experience. The results showed that CWA could pick out spectral signals that may be utilized to differentiate between the three different stressors. Overall accuracy (OA) results showed that anthracnose had the highest OA (94.12–94.28%), followed by tea green leafhopper (93.99–94.20%) and sunburn damage (90.26–90.69%) (82.50–83.91%). This indicates that hyperspectral imaging can be used to identify plant phenotypes following pathogen or insect infestation. The research vacuum in the realm of disease modeling and classification is addressed by M. Bhagat et al. [27], who write about the several diseases that can affect leaves, what causes them, how diseases are classified, and what potential solutions there may be. Summary of few work related to proposed work have been presented in Table 1.

3 Proposed methodology

The method presented consists of 3 main stages namely: image pre-processing, feature extraction and classification. Figure 1. represents the flow of the proposed work. Leaf image is preprocessed using image processing techniques like image conversion, resizing. Forty samples of each kind of tea disease were chosen for this experiment. Disease spot images are extracted from 120 randomly chosen images. The images of disease spots are divided into two groups; the first 20 are used for training, and the second 20 are used for testing. Since VGG-16's feature extraction is deep learning-based, our trained models benefit greatly from the architecture's use. Since the available data is extremely sparse, we had to resort to image augmentation methods to boost the sample size by a factor of 14. In order to get features from the augmented dataset, we used the VGG-16 model. We have used a variety of machine learning based classifiers, including KNN, Random Forest, XGBoost, and Kernelized support vector machine, to accomplish classification. The various steps involved in the proposed work are explained below in subsections 3.1, 3.2 and 3.3.

3.1 Preprocessing

All the sample images are resized to 224*224 in this phase. This is done for fast processing of images in various further steps. It also reduces use of storage. The algorithm of the proposed model is presented below as:

Input: *Tea leaf images*
Output: *Performance evaluation metrics*
Procedure:
Step − 1 *for all input images, split into training and testing images*
Step − 2 *Preprocess both training and testing images*
Step − 3 *Extract VGG − 16 features*
Step − 4 *Build model based on VGG − 16 training features*
Step − 5 *Apply KNN, XGB, RF, Kernel SVM algorithm on build model*
Step − 6 *Compare the obtained results in terms of accuracy, precision etc.*
End

3.2 Feature extraction

The goal of the feature extraction stage is to extract the features from the images in the dataset. The advantages of Feature Extraction stage are it improves the accuracy, reduces

Table 1 Summary of related work on tea leaf dataset

Reference	Techniques used	Dataset	Contributions
Hossain et al. [15], 2018	random forest, adaboost, decision trees, and support vector machine	Bangladesh tea leaf images	Identified brown blight disease and algal leaf disease are two of the most prevalent ailments that affect tea leaves
Hu, Gensheng, et al. [6], 2019	SVM, C-DCGAN	Tea leaf	On average, a VGG16 deep learning model trained using enhanced illness spot images can correctly identify diseases in tea leaves with a success rate of 91%
Wang, Tao, et al. [23], 2021	R-CNN) Mask-RCNN, FPN, RPN	Tea leaf	Correctly identified tea leaves and buds
Hu, Gensheng, et al. [24], 2021	discriminative pyramid (DP) network-based technique	Tea leaf	By utilizing a pyramid attention network, it is able to overcome the difficulties posed by tea geometrids with extreme variations in shape and size as well as small, hard-to-detect targets
Hu, Gensheng et at. [25], 2022	multi-convolutional neural network (CNN) model, MergeModel,	Tea leaf	The MergeModel had excellent accuracy in distinguishing between infected and healthy tea leaves, and in identifying common tea leaf ailments like white scab, tea leaf blight, red scab, and sooty mould
Zhao, Xiaohu, et al. [26], 2022	Hyperspectral imaging, Continuous wavelet analysis (CWA)	Tea leaf	In comparison to the traditional optical detection method, hyperspectral imaging facilitates efficient and non-destructive plant monitoring. Spectral signals that may be utilized to differentiate between the three categories of stressors were found by CWA
Xuechen Zhang et al. [35], 2023	FTL, DELTA parallel robotic arm, CNN	Tea leaf	A robot that uses a deep learning algorithm and the DELTA parallel robotic arm to sort machine-picked FTLs into grades online is introduced. For the machine-picked FTLs, they developed a quick CNN-based identification and location method with regional segmentation, and got actual identification accuracy values up to 96%

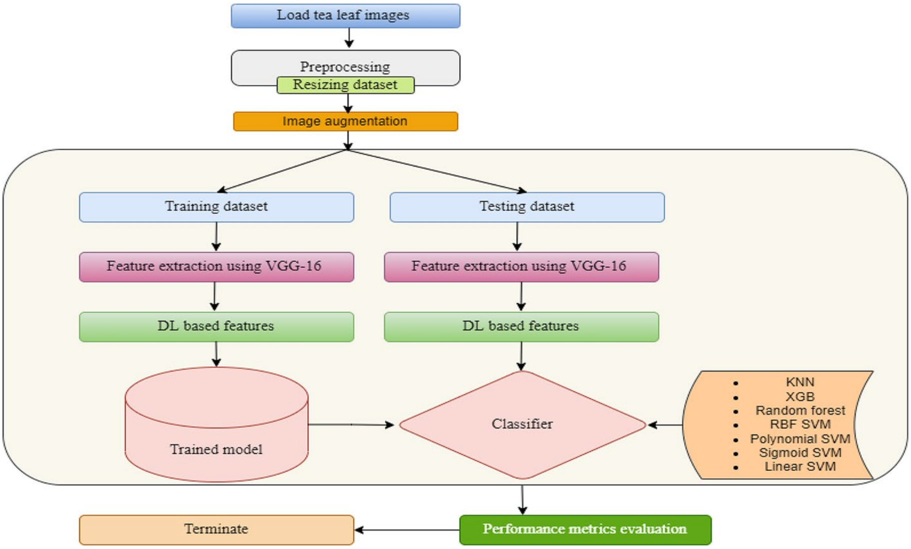


Fig. 1 Flow of proposed work

the risk of over-fitting, speeds up the training, improves data visualization, increases the explain-ability of the model.

VGG-16 The Visual Geometry Group network (VGG-16) can be used as a feature extractor with a high level of accuracy. Figure 1 shows how it is put together. The image that goes into the VGG-16 network is always the same size, which is 3*224*224. It is sent through a stack of layers with different receptive fields that are connected in a way that looks like a spiral. In the VGG-16 network, the stride rate stays the same for both the convolutional layers and the pooling layers, which are 33 with stride 1 in the convolutional layer and 22 with stride 2 in the pooling layer. The first two convolutional layers have 64 filters and the third has 128 filters. The last three layers of convolutional layers each have 256, 512, and 512 filters. Before each convolutional operation, border pixels are filled in with zeros. This keeps the size of the feature maps the same as the size of the input. At the end of the VGG-16, there are three layers that are all connected. The first two FC layers are made up of 4096 neurons, while the last FC layer squeezes the features down to 1000 dimensions [28, 29, 36] (Fig. 2).

Softmax Function Softmax function: In neural computing, the Softmax function is another sort of activation function. It is used to figure out how likely something is based on a set of real numbers. The output of the Softmax function is a range of numbers from 0 to 1, with the sum of the probabilities being 1. The relationship is used to figure out the Softmax function [30, 31].

$$f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_i}}$$

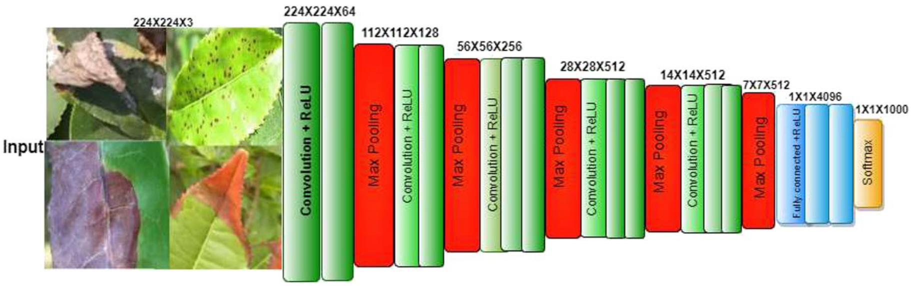


Fig. 2 VGG-16 network architecture for feature extraction [28]

The Softmax function is used in models with more than one class. It gives the probability of each class, with the highest probability going to the target class. Most of the time, the Softmax function is used in almost all the output layers of deep learning architectures. The main difference between the Sigmoid and Softmax activation functions is that the Sigmoid is used for binary classification and the Softmax is used for multivariate classification.

ReLU Since its proposal in 2010 by Nair and Hinton, the rectified linear unit (ReLU) activation function has been the most popular activation function for deep learning applications, producing state-of-the-art results [30, 32]. The ReLU is the most popular and commonly utilized function, and it is also the fastest learning AF. In comparison to the Sigmoid and tanh activation functions, it provides superior performance and generalization in deep learning. Since the ReLU is a near-linear representation of the underlying function, it retains the characteristics of linear models that make them amenable to optimization via gradient descent [30, 31]. The ReLU activation function is given by

$$f(x) = \max(0, x) = \begin{cases} x_i, if x_i \geq 0 \\ 0, if x_i < 0 \end{cases}$$

where x_i is an input element and 0 is the value assigned to x_i if it is less than 0.

To solve the vanishing gradient problem seen in previous iterations of activation functions, this function inverts inputs less than zero. Common applications of deep neural networks include object categorization and voice recognition, and the ReLU function has been utilized within the hidden units of these networks in conjunction with another activation function used in the network's output layers. The primary benefit of utilizing rectified linear units in computation is that it guarantees faster calculation due to the elimination of the need to compute exponentials and divisions. As it squeezes the values from zero to one, the ReLU also introduces sparsity in the hidden units, which is another one of its features. Rectified networks enhanced deep neural network performance, however the ReLU has the drawback of being easily overfit compared to the sigmoid function. The dropout approach has been employed to mitigate this impact. Although (Nair and Hinton, 2010) noted that the ReLU has been utilized in several architectures due to its simplicity and reliability [30, 32], the ReLU and its derivatives have been employed in various architectures of deep learning, including the limited Boltzmann machines. A major drawback of the ReLU is that it is fragile, leading to the death of some gradients during training. As a result, certain neurons become inactive, which prevents them from activating in future data points and impedes learning [30, 31]. The leaky ReLU was presented as a solution to the problems caused by dead neurons.

3.3 Classification

The different classifier used in this work are explained below in detail along with their mathematical equation, architecture, uses, limitations etc.

KNN It's an instance-based learning classification algorithm. It uses distance function as a similarity measure and classifies new case based on this from all the stored cases. Majority votes by neighbour classes determine how the instance must be classified. The value of k should not be too small as it will be sensitive to noise points. Generally high value is preferable, according to thumb rule it should be sqrt(n), where n is number of populations. The different distance functions could be:

Euclidean	Manhattan	Minkowski
$\sqrt{\sum_{i=1}^{k}\left(x_i - y_i\right)^2}$	$\sum_{i=1}^{k}\lvert x_i - y_i\rvert$	$\left(\sum_{i=1}^{k}\left(\lvert x_i - y_i\rvert\right)^q\right)^{\frac{1}{q}}$

XGBoost As an extension of gradient boosting, XGBoost is a supervised algorithm that makes use of ensemble trees. For "Extreme Gradient Boosting," see XGBoost. Due to its high performance, speed, and generalizability, it is widely used as a classifier in machine learning. Using a regularisation term and a loss function, it seeks to find the optimal cost objection function. Gradient Boosting Framework is an implementation of the GBDT model and generalised linear machine learning algorithms. The core component of the GBDT model is the regression tree, also known as a classification and regression tree [33] (Fig. 3).

XGBoost [37] is the extension of GBM. GBM segregates the optimizing problem in two steps that is finding the direction of the step in first part and then optimization of the step in second part whereas XGBoost calculates the step by below equations:

$$\frac{\partial L(y, f^{(m-1)}(x) + f_m(x))}{\partial f_m(x)} = 0$$

Calculating the Taylor expansion in second order for $f^{(m-1)}(x)$, the equation obtained is:

$$L\left(y, f^{(m-1)}(x) + f_m(x)\right) = L\left(y, f^{(m-1)}(x)\right) + g_m(x) f_m(x) + \frac{1}{2} h_m(x) f_m(x)^2$$

Gradient is represented as $g_m(x)$ and Hessian by $h_m(x)$:

$$h_m(x) = \frac{\partial^2 L(Y, F(x))}{\partial f(x)^2}_{f(x)=f^{(m-1)}(x)}$$

The equation is rewritten as:

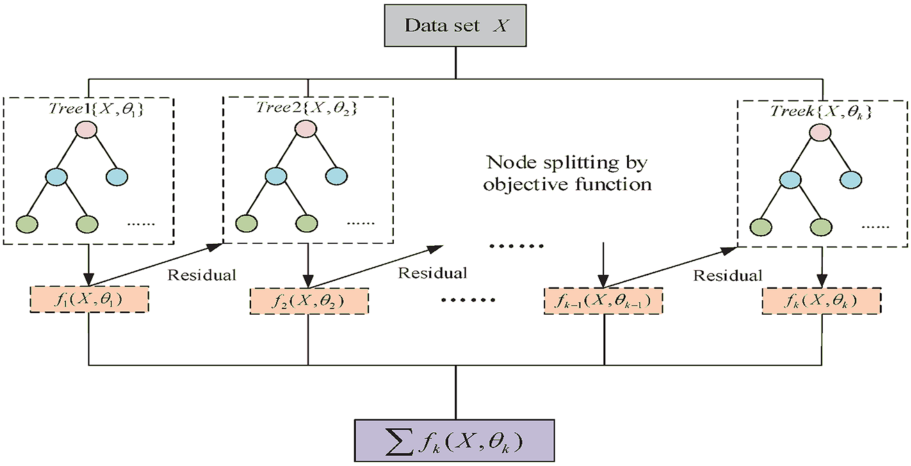


Fig. 3 Working of XGBoost

$$L(f_m) \approx \sum_{i=1}^{n}[g_m(x_i)f_m(x_i) + \frac{1}{2}h_m(x_i)f_m(x_i)^2] + const. \propto \sum_{j=1}^{T_m}\sum_{i\in R_{jm}}[g_m(x_i)w_{jm} + \frac{1}{2}h_m(x_i)w_{jm}{}^2]$$

Random Forest Random Forest is a combination of a large number of decision trees and hence it is like ensemble. In Random Forest each tree gives out a class prediction and the one with majority votes becomes model for prediction.

$$I_{secondlayer} = \frac{n_{left}}{n_{parent}} * I_{leftnode} + \frac{n_{right}}{n_{parent}} * I_{rightnode}$$

SVM SVM algorithm classifies new data points on finding optimal one from the hyper-planes generated. The input space is transformed to high dimensional space in SVM [34] using kernel trick to deal with non-linear and inseparable planes. The kernels used are:

Support vector machine kernel		
Linear Kernel	Polynomial Kernel	**Radial Basis Function Kernel**
$K(x,x_i) = sum(x * x_i)$	$K(x,x_i) = 1 + sum(x * x_i)^d$ where `d' is degree of polynomial	$K(x, x_i) = \exp\left(-gamma * sum\left((x - x_i^2)\right)\right)$ where gamma value lies between 0 and 1

The equation for hyper line is $w.x + b = 0$ which is same as $w.x = 0$ (which has more dimensions). To separate into classes, the following equation is used.

For each vector $X_i either$:

$$W.X_i + b \geq 1 for X_i having the class 1 \text{ or } W.X_i + b \leq -1 for X_i having the class - 1$$

(a) Tea leaf blight (b) Tea red leaf spot (c) Tea red scab

Fig. 4 Few samples of tea leaf disease dataset

4 Dataset

In this work, we have referred dataset from our base paper [6]. The tea leaf disease images in the base paper were shot at Tianjingshan National Forest Park, south of Hefei, Anhui Province's capital, and surrounded by Chaohu Lake, one of China's five major freshwater lakes. It's 31°14′37″ north, 117°36′16″ east, and 40 m above sea level. Canon EOS 80D SLR and DJI phantom 4pro with 10-m flight altitude are image acquisition devices. The tea leaf's disease images also came from Anhui's pest and disease database. The selected dataset contains three types of diseases such as tea red scab, tea red leaf spot, and tea leaf blight [6] (Fig. 4).

5 Results and Discussion

The results of our suggested model's individual steps are discussed below. The procedure begins with the submission of datasets, continues through preprocessing, feature extraction, and ends with a successful classification using a Random Forest classifier. Measures of a model's efficacy include its sensitivity, precision, specificity, accuracy, F1 Score, and so on. The model, dataset, challenge, and context all play a role in deciding which performance indicators to utilize. Below, we detail the measures of success utilized to assess our suggested model.

$\boldsymbol{\alpha}$ = Number of Abnormal images classified rightly.	$\boldsymbol{\beta}$ = Number of Normal images classified rightly.
$\boldsymbol{\gamma}$ = Number of Normal images classified as Abnormal	$\boldsymbol{\delta}$ = Number of Abnormal images classified as Normal.

Confusion Matrix The True Positive, True Negative, False Positive, and False Negative counts are all shown in a confusion matrix.

Metric	Description	Formula
Accuracy	When the number of FPs and FNs in a dataset are almost equal, accuracy is utilized as a metric. It is the fraction of the model's predictions that came true.	$\frac{\alpha+\beta}{(\alpha+\delta)+(\beta+\gamma)}$

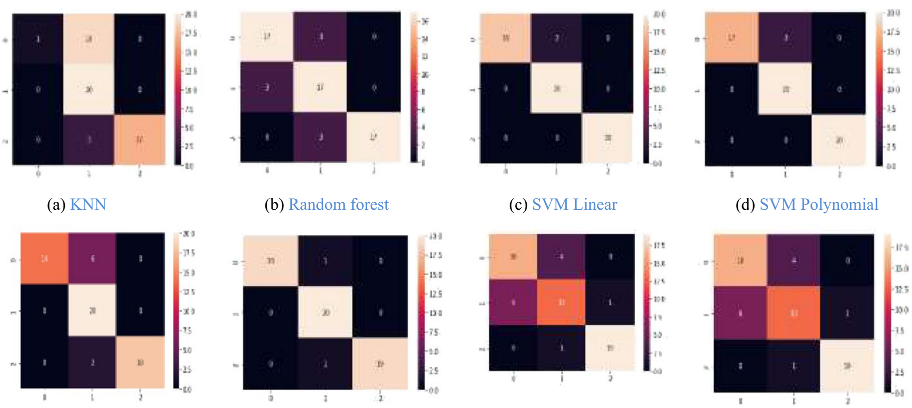
Metric	Description	Formula
Sensitivity/Recall	Sensitivity is the percentage of correct diagnoses as opposed to the total number of positive diagnoses.	$\frac{\alpha}{\alpha+\gamma}$
Precision	When false positives cannot be tolerated, precision measurements become applicable. To put it another way, precision is the proportion of true positives to all expected positives.	$\frac{\alpha}{\alpha+\delta}$
Specificity	When all possible false negatives must be accounted for, specificity is the best metric to use. To put it simply, it is the proportion of true negatives to all negatives considered.	$\frac{\beta}{\beta+\gamma}$
Execution time	The execution time of sample prediction is calculated by subtracting start time of the algorithm from end time of the algorithm.	$End\ time - Start\ time$

Image pre-processing, feature extraction, and classification are the three primary pillars of the described method. The proposed process is depicted in Fig. 1. Images of leaves are converted and resized, among other image processing preparations. Forty examples of each kind of tea illness were chosen for this trial. In order to gather photos of illness spots, we choose all 120 images. A total of 40 illness spot photos are collected; 20 are utilized for training, and the remaining 20 are used for testing. The proposed model's classification accuracy is compared to that of other researchers' published results (Fig. 5).

The accuracy obtained with VGG-16 features and KNN, RF, XGB, RBF, Polynomial, linear and sigmoid kernel based SVM classifier for tea leaf dataset are 63.33%, 85%, 80%, 80%, 95%, 96.67% and 96.67% respectively. The performance metrics are tabulated in the Table 2.

In Fig. 6, we provide some of our model's predictions on the provided datasets. Model classes are validated against their appropriate dataset levels in test cases.

We have compared our present work with existing work of Hu, Gensheng et al. [6] taking same dataset. We have made comparative study of techniques adopted by the authors [6] and their classification accuracy achieved with the same of present model in Table 3. Graphical representation of performance of different classifier with VGG-16



(a) KNN (b) Random forest (c) SVM Linear (d) SVM Polynomial

(e) SVM Polynomial(d=8) (f) SVM Sigmoid (g) XGB (h) SVM RBF

Fig. 5 Confusion matrix obtained in different classifiers

Table 2 Performance metrics of the proposed work

Dataset	Classifier		Accuracy	Precision	Recall	$F_1 - score$	Execution time(ms)
Tea leaf	KNN		0.6333	0.6333	0.6333	0.6333	0.034
	XGB		0.8000	0.8000	0.8000	0.8000	0.025
	Random Forest		0.8500	0.8500	0.8500	0.8500	93.38
Dataset	*Classifier*	*Kernel*	*Accuracy*	*Precision*	*Recall*	$F_1 - score$	*Execution time(ms)*
Tea leaf	SVM	RBF	0.8000	0.8000	0.8000	0.8000	0.035
		Polynomial (Degree = 8)	0.8667	0.8667	0.8667	0.8667	0.035
		Polynomial	0.9500	0.9500	0.9500	0.9500	0.038
		Linear	0.9667	0.9667	0.9667	0.9667	0.079
		Sigmoid	0.9667	0.9667	0.9667	0.9667	0.037

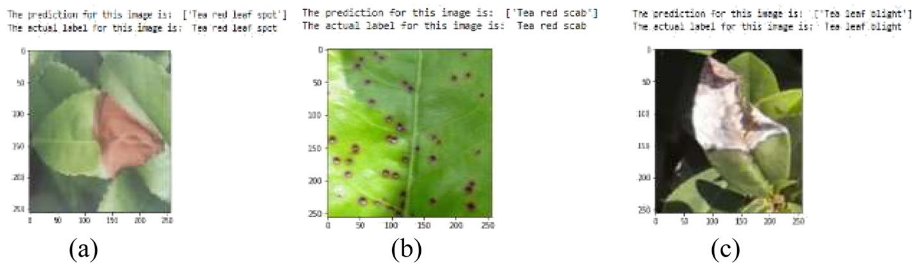


Fig. 6 For tea leaf dataset, classified disease (a) shows red leaf spot and (b) shows red scab (c) shows leaf blight

Table 3 Performance Comparison of existing work and proposed method

Author's	Techniques	Classification accuracy (%)
Hu, Gensheng et. al. [6], 2019	SVM + improved C-DCGAN + VGG-16 classifier	91.00
Proposed Technique	VGG-16(CNN) features + Kernel SVM	96.67

features for Tea leaves and the achieved percentage classification accuracy in various articles along with proposed methods is shown in Figs. 7 and 8 respectively.

There has not been a lot of study done on how to categorize tea leaf diseases. Our work has been compared to those of other authors who have used the same tea leaf dataset but different methods. Disease detection deep learning model VGG16 can be improved with new training samples generated by conditional deep convolutional generative adversarial networks (C-DCGAN), as demonstrated by Hu, Gensheng et al. [6]. Experiments show that the SVM can segment disease spot images under low shot

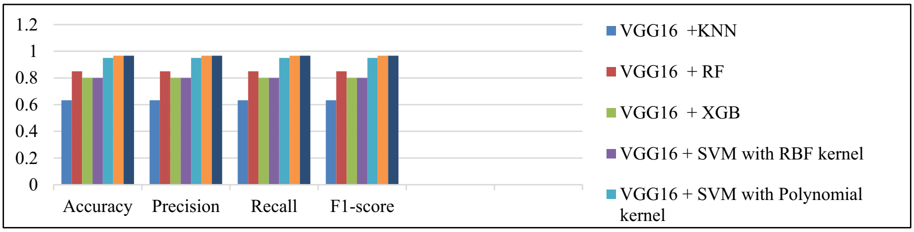


Fig. 7 Graphical Representation of performance of different classifier with VGG-16 features for Tea leaves

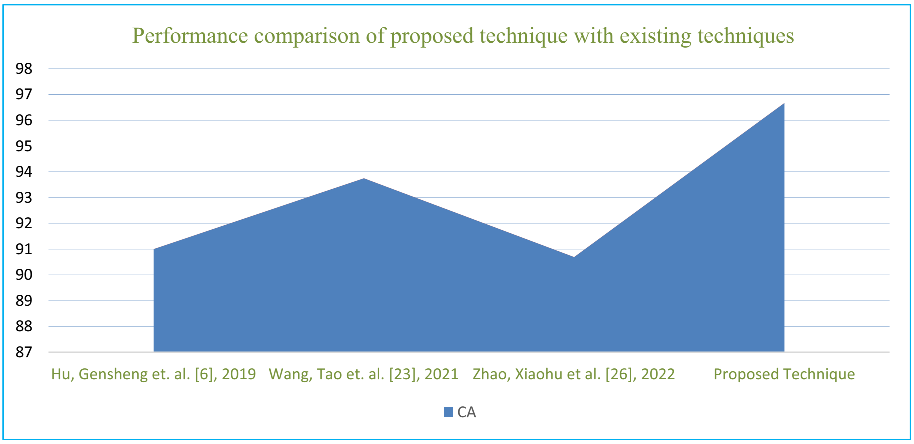


Fig. 8 Graph showing achieved percentage classification accuracy in various articles along with proposed methods

learning conditions while retaining the edge information well, the improved C-DCGAN can generate augmented images with the same data distribution as real disease spot images, and the VGG16 deep learning model trained with augmented disease spot images can accurately identify tea leaf's diseases, with an average identification accuracy of 91%.

With the tea leaf dataset, we propose a model that uses VGG-16 to extract color features. Modeling is performed based on this feature, and then a number of machine learning-based classifiers, including KNN, XGB, Random Forest, and kernelized SVM, are used to perform the classification. With Sigmoid and Linear kernel-based SVM and VGG-16 features, our proposed model achieved best classification accuracy. For the tea leaf dataset, the accuracies obtained using KNN, RF, XGB, RBF, Polynomial, linear, and sigmoid kernels in a support vector machine (SVM) classifier are 63.33%, 85%, 80%, 80%, 95%, and 96.67%, respectively. Proposed model has a high degree of accuracy (96.67%). Furthermore, this precision is achieved through a classic machine learning based classifier. Below is a graph displaying the results of using different machine learning based classifiers with VGG-16 features on the tea leaf dataset. Kernel methods using an RBF kernel have a runtime complexity of $O(n * s)$. When accuracy is more important than runtime complexity yet the number of support vectors is enormous, users are typically compelled to resort to linear algorithms with $O(s)$ prediction complexity. It takes $O(n^d)$ time to run the polynomial kernel. In this case, n represents the total number of support vectors, s represents the input dimension, and d represents the polynomial degree. Here, it should be noted that classification accuracy is enhanced by 5.67% on the same dataset by using our proposed model.

6 Conclusion

In this work, we have proposed a hybrid technique that combines deep learning-based features of augmented dataset with machine learning based classifier for getting better classification result. In proposed work, VGG-16 is used for colour feature extraction from the tea leaf dataset. Based on this feature, model is built and several machine learning-based classifiers like KNN, XGB, Random Forest, and kernelized SVM are employed for classification task. Our proposed model achieved highest classification accuracy with Sigmoid and Linear kernel based SVM and VGG-16 features. The accuracy obtained with VGG-16 features and KNN, RF, XGB, RBF, Polynomial, linear and sigmoid kernel based SVM classifier for tea leaf dataset are 63.33%, 85%, 80%, 80%, 95%, 96.67% and 96.67% respectively. The accuracy of proposed model is 96.67%. We compared our proposed work with existing work on tea leaf dataset and found that our model is performing comparatively better. Farmers can take prophylactic actions against the spread of plant diseases with the help of the proposed model. Multiple works are compared to the categorization accuracy achieved by the suggested approach. It is clear that the proposed method is effective for the provided leaf images, and the accuracy gained is higher than that of previous methods. In future, we plan to combine additional handcrafted features to achieve the same or higher level of accuracy across additional datasets.

Funding This study received no specific financing from governmental, private, or non-profit funding bodies.

Declarations

Conflicts of interest There are no conflicts of interest declared by the authors.

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