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# An Intelligent Framework for Herb Leaves Classification

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**Abstract:** The grouping result is low for picture handling in the current strategies, so the proposed model has been created to further develop the characterization results. Orders of the leaf were done in light of the removed highlights. Thus, a novel Ant Colony found Gradient Boosting Model (ACbGBM) is developed with required processing parameters: filtering and classification functions to improve the classification performance and make the system more robust and efficient. In this model, better classification results were obtained and are shown in the result section. Here, leaf data is collected and initialized to the system. In this manner, pre-handling is finished over the introduced informational collection after highlight extraction. The negligible elements are taken out in highlight extraction, and the entire significance highlights are picked. The extracted features' fitness is contrasted with the fitness of ants. After that, classification is done over the extracted features. Besides, a contextual investigation is created to make sense of the functioning technique of the proposed model. As a result, the constructed model was implemented in the MATLAB programme, and the recall, accuracy, precision, error rate, and f-measure were all measured in its presence.

***Keywords*** *Ant Colony Optimization · Pre-processing · Feature Extraction · Leaf Type Classification · Data Initialization*

## 1 Introduction

Herbs may be grown everywhere with suitable soil and water to support their growth [1]. This means medicinal plants can be found in any region of the nation [2]. Since ancient times, traditional medicines derived from herbs have primarily been used to treat various disorders that could not be healed using other medical treatments [3, 4]. Herbal species were thought to be the most effective plants for treating medical conditions and cleaning the air [5] since they kill germs and other pollutant emissions that are hazardous to living. In addition, to provide food and shelter, many plants also have medicinal properties and may be used to cure disorders [6]. When recognizing and categorizing flowering plants, the shape is regarded as the most crucial trait [7].

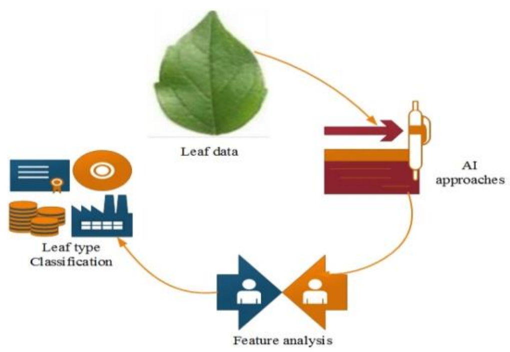


**Fig. 1** Herbal leaves classification

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The herbal leaves classification system with the Artificial intelligence (AI) system is described in Fig. 1. Since this function is always available, most researchers have used it in their investigations [8, 9]. In this study, the primary focus is on extracting characteristics from medicinal herbs, followed by machine training [10, 44]. It is believed that there are over 2,000 different types of medicinal herbs, many of which have not yet been thoroughly researched [11, 45]. There are hardly many plants that have had their therapeutic and curative powers verified by scientific research [12]. Characterization and categorization of herbs are of utmost significance when herbs are utilized in developing products for ingestion by humans or application topically [13, 46]. Because of this, the protective effects of products derived from herbs, particularly traditional medicines, are significantly proportional to the density of the psychoactive chemical in those herbs [14, 47]. Traditionally, herbal leaves classification has been done manually, by experts who have extensive knowledge and experience in botany and plant science [15]. In any case, progresses in innovation and picture handling have made it conceivable to robotize this cycle utilizing PC vision and AI procedures [16]. These techniques can be used to extract characteristics from leaf images, and then those characteristics can be used to categorise the leaves into various groups. [17, 18]. However, most medicinal herbs on the market, even those sold in natural medicines stores, are only available as dead leaves, barks, and roots [19, 48]. Moreover, it was utilized in powdered components, mixes, or extracts. This is the case even when the plants are sold [20, 49]. These varieties of herbs can be difficult to identify, and there is a possibility that they have been contaminated with other, less expensive materials [21, 22]. The herb leaf classification utilizes a novel superpixel-based approach for extracting color and spatial features, which improved the detection of salient objects within the images and resulted in higher classification accuracy [30, 31]. The event summarization in videos effectively utilizes herb leaf classification to identify and extract relevant frames for summary generation [32, 50]. The Deep and crowded Anomaly Detection (D-CAD) method was able to accurately classify herb leaves with a high level of precision and recall [33, 34]. Several, Deep learning (DL) [35] and machine learning (ML) [36] models, such as the recurrent neural model [37, 38], neural convolution model [39, 40], etc., Have been introduced in the past to classify the herbal leaf type. But high complexity and computation time have been recorded. So, the current study has aimed to develop an optimized boosting system for herbal leaf classification. The motivation for developing an Ant Colony Optimization (ACO) based Gradient Boosting Model (GBM) would be to combine the strengths of both ACO and GBM in order to create a more efficient and accurate machine learning model. The ant-inspired meta-heuristic algorithm ACO is very effective at resolving optimisation issues. It has been successfully applied to various fields, such as routing, scheduling, and feature selectionA strong model is created by combining several weak learners using the effective ensemble learning technique known as GBM. It has been widely used for various tasks, such as regression, classification, and survival analysis. By joining the qualities of ACO and GBM, an ACbGBM model might actually work on the accuracy and effectiveness of the educational experience by utilizing ACO to streamline the determination of elements and the boundaries of the GBM. Additionally, ACbGBM model could be used in high dimensional or noisy datasets, where traditional optimization methods fail. In synopsis, the inspiration for fostering an ACbGBM model is to work on the exactness and effectiveness of the AI cycle by consolidating the qualities of both ACO and GBM, and to have the option to deal with high layered and uproarious datasets. The introduction regarding this result was presented in section 1, and five recent kinds of literature related to this work were developed in section 2. Also, segment 3 was the framework model, and the issue and the proposed plan of the model were made in area 4. The outcome and conversation of the exploration were introduced in segment 5, and the review's decision was created in area 6.

## 2 Related Works

The following are a few recent publications that discuss the taxonomy of herbal leaves:

Herbal leaves of the same species can exhibit significant variations in shape, size, and color, making it challenging to classify them accurately. Thus, Amgad M et al. [23] fostered a programmed and effective grouping framework for recognizing Malaysian spices that can be used in clinical or culinary fields. In the proposed framework, different classifiers were assessed to develop a proficient classifier, and consequently, the classifier was consolidated with a portable application to improve on constant characterization. The experimental outcomes showed that for both the experimental model and the created mobile application, the SVM classifier achieved a recognition accuracy of 74.63% and the DLNN classifier acquired a recognition accuracy of 93%.

Environmental elements like lighting and humidity have an impact on herbal leaves, which can lead to differences in their appearance and make it challenging to categorise them. So, Li et al. [24] has proposed an efficient framework to quantify the conformal prediction and prediction reliability was enhanced with the CP-KNN (CP with kNN). A new method called "conformal prediction with shrunken centroids (CPSC)" had been proposed to address limitations in existing methods. CPSC regularized class centroids to diminish the effect of unimportant highlights and psychologist the example space for expectations and unwavering quality measurement. To assess the exhibition of CPSC, it was contrasted with another technique called "CPKNN" utilizing an order task with 12 classes of elective natural medication and electronic nose information. Online prediction with data augmentation, where unlabeled data was filtered to augment the training data based on prediction reliability and the final accuracy of the testing set was compared, and offline prediction with fixed testing set accuracy evaluation comprised the two tasks involved in the comparison.

Nature has given clinical plants and assumes a huge part in the battle against sicknesses. Natural plants are normally difficult to recognize their reality on the off chance that they are as yet filled in a nursery. The shortage of individuals' understanding of herbal plants usually creates an unexploited supply of herbal leaves needed to assist as different and supportive medicine. In this way, Fekri Ershad [25] has proposed a method for bark surface characterization with high accuracy based on the upgraded neighborhood ternary examples (ILTP). The ILTP proposed used a technique where ternary examples were changed into two paired designs, which were then separated into uniform and non-uniform gatherings. These examples were then relegated names in view of their level of consistency, and the probability of these marks was utilized as a component. The methodology likewise integrated a multi-layer perceptron with four hypotheses for deciding the quantity of secret hubs. Results from tests on two benchmark datasets demonstrated that this approach yielded better grouping precision contrasted with generally utilized techniques.

Mukherjee et al. [26] said that the framework caught the leaf pictures in oversaw brightening, and handled leaf pictures are taken care of to the customary brain frameworks to group a wide range of leaves. The category was verified and repeated by test runs and tenfold cross-validation methods. Anyhow, due to linear transformation, the correlation still exists.

Azania and Kheiralipour [27] explained the classification of the most popular herbal plants. Nutrient features, as well as easy convenience, arise due to paying attention to the medical plants. The Smartphone vision system captures the plant pictures. The leaves are classified by color, shape, and size characteristics of the images. The effectiveness of the implemented design was about 100 % in connection with the coefficient and meant a square error rate of 1.00 plus $2.35 \times 10^{-12}$ correspondingly. However, it has a high correlation between channels.

Increasing urbanization and population growth have become nurtured. The plants and growing the plants were essential for human beings. So, it is necessary to protect the plants of global importance environmentally and economically. Thus, Kour and Aror [28] said that the method of segment classification in plants uses leaf images. In the first base, actual pictures and photos among the crowded statics are stored and processed to remove the noise features and improvement. At the second base, altered characteristics related to the color and appearance was extracted. In the third base, the images were segmented through k-means algorithms. The fourth base contains the machine's testing and the training performed. This method achieves high experimental results. Yet, have the same singularity problem as other nonlinear transformations.

People know about the backyard herbal planets and their values. Technology is used to see the importance of plants. So, Sachar and Kumar [29] said that the leaves images captured by the mobile phone with dust, shadow, and hidden other leaves. Pros and cons categorize this technique. This technique contains different areas for improvement. Anyhow, the correlation between channels is not suitable for color image processing.

The critical commitment of this current review is made sense of as follows,

- A novel approach for Intelligent Framework for Herb Leaves Classification has been developed, which is called Ant Colony based Gradient Boosting Model (ACbGBM) was designed with required processing parameters: filtering and classification functions to improve the classification performance and make the system more robust and efficient.
- The curiosity of the ACbGBM approach is that it utilizes the ACO calculation to streamline the boundaries of the GBM model, for example, the quantity of choice trees, the most extreme profundity of the choice tree, and the learning rate. As a result, the algorithm is able to identify the ideal set of variables that produce the best accuracy and generalisation.
- • The unique leaf features were then extracted during the feature extraction stage and displayed in the classification layer after the pre-processing was finished.
- Finally, the types of herbal leaves have been categorized, and the classification robustness has been measured. Here, the performance improvement has been validated in terms of F-measure, precision, error rate, accuracy, and recall.

### 2.1 Research gap

One potential research gap in the field of herb leaves classification is the lack of robust methods for identifying and classifying rare or endangered plant species. Many current approaches rely on large datasets of labeled images, but these may not include a diverse range of species or may not accurately represent the variability within a given species. Developing new methods for identifying and classifying rare or endangered plant species, such as using a combination of visual and molecular data, could improve conservation efforts and our understanding of plant biodiversity. Additionally, there is a gap in research on the use of DL techniques for herb leaves classification, as well as a lack of studies on the performance of these methods under various environmental conditions and with different types of imaging equipment. One more examination hole could be the advancement of strategies for programmed recognition and order of spice leaves in wild, common habitats with negligible human mediation.

## 3 System Model and Problem Statement

A few characterization models were used for recognizing the spice leaf types, however the mind boggling pictures have made the grouping a dangerous undertaking. Hence, the low classification exactness has been recorded. These issues have spurred this current review to execute the helping calculation with the advancement capability to arrange natural leaf types with high precision scores. Here, the enhancement capability is used in the arrangement period of the helping component that has offered the most adequate order result. When comparing this research with other existing models, fewer classification results are considered a demerit. To overcome the demerit mentioned, the above-proposed model was developed. Through the proposed model, higher classification accuracy was attained. In this manner, the fundamental framework model with the issue was represented in Fig. 2.

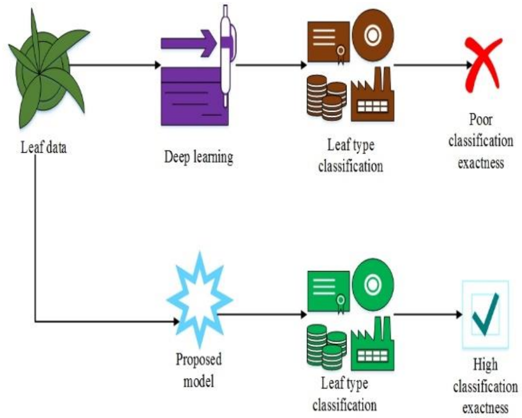


**Fig. 2** System model with problem

## 4 Proposed Methodology

A novel Ant Colony-based Gradient Boosting Model (ACbGBM) has been planned to execute for classifying herbal leaves and their classification from the trained leaves image data. The trained leaf images were primarily pre-processed to remove the present noise features. Then its features are extracted, and classification is performed in the classification phase. Here, the presence of ant colony fitness has provided the best specification outcome. The performance indicators were tested and evaluated against other published works in the end. Additionally, Fig. 3 describes the suggested architecture in detail.

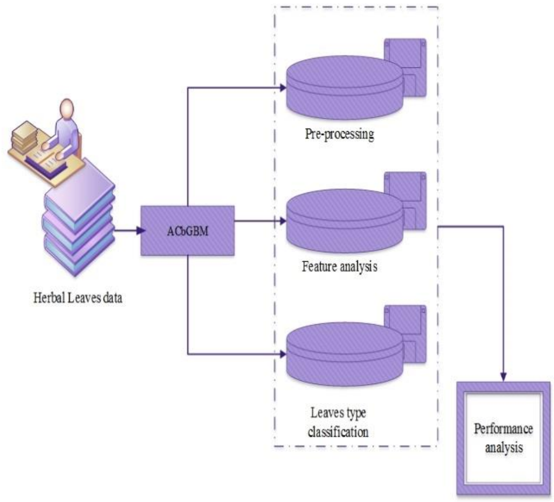


**Fig. 3** Proposed architecture

A metheuristic optimisation method called the Ant Colony Optimisation (ACO) algorithm was developed as a result of studying how ants find food. It is a multitude knowledge based calculation that mirrors the way of behaving of insects in finding the most limited way from the settlement to a food source. The ACO calculation has been utilized in different improvement issues, for example, the mobile sales rep issue, vehicle steering issue and some more. The proposed Ant Colony based Gradient Boosting Model (ACbGBM) is a novel approach that combines the ACO algorithm with the Gradient Boosting Model (GBM) to improve the performance of herbal leaves classification GBM is a potent machine learning technique that has been extensively applied to a variety of tasks including speech recognition, image classification, and natural language processing. GBM is an ensemble of decision trees and it builds the model in a stage-wise fashion by adding one decision tree at a time. The curiosity of the ACbGBM approach is that it utilizes the ACO calculation to advance the boundaries of the GBM model, for example, the quantity of choice trees, the most extreme profundity of the choice tree, and the learning rate. As a result, the algorithm is able to identify the ideal set of variables that produce the best accuracy and generalisation. The ant colony optimisation technique is also used by the ACbGBM approach to choose the most crucial features from a huge feature space. The GBM model performs better thanks to the feature selection step's contribution to the reduction of the data's dimensionality. The proposed model (ACbGBM) was created to increment grouping accuracy. At first, the home grown leaves information were gathered and brought into the framework. Then, at that point, the proposed plan was created to play out the pre-handling and element extraction capability. After extracting the elements, the leaves type was classified. Consequently, the performance of the implemented model was measured. Accuracy, recall, precision, F-measure, and error rate were used to gauge the design's performance. The revised manuscript's Figure 4 depicts the workflow model.

Leaf classification is a task in which the goal is to classify different types of leaves based on their characteristics. This task is important in various fields such as plant taxonomy, ecology, forestry, and agriculture. For instance, in plant scientific categorization, leaf arrangement can be utilized to distinguish and group various types of plants. In ecology, leaf classification can be used to study the distribution and diversity of plant species in a particular area. In forestry, leaf classification can be used to identify and track different types of trees in a forest. In agriculture, distinct varieties of crops can be identified and categorised using leaf classification. The effectiveness and applicability of a method to a given situation will determine whether or not the scientific community chooses to adopt it for leaf categorization. If the proposed approach of Ant Colony-based Gradient Boosting Model (ACGBM) has been demonstrated to be efficient in leaf classification tasks and if it has some advantages over alternative methods, then it might be helpful for the scientific community. The writers ought to exhibit the presentation and the upsides of their proposed strategy in contrast with the current techniques in their article.

There have been various specialized leap forwards in the field of Spice Leaves Characterization, including the utilization of DL procedures, for example, convolutional brain organizations (CNNs) and move learning. These methods have been shown to achieve high levels of accuracy in classifying herb leaves, even when working with limited data sets. Other breakthroughs include the development of new feature extraction methods, such as the use of texture analysis and shape analysis, as well as the use of domain adaptation techniques to improve performance on specific types of herb leaves. Additionally, various pre-processing steps like data augmentation, data normalization and fine tuning of hyperparameters have been proved to be beneficial to improve model performance. ACbGBM has been utilized to upgrade the boundaries of different AI calculations, for example, choice trees and brain organizations, to work on their presentation on the undertaking. Finding near-optimal solutions in huge search spaces is one of ACbGBM's primary advantages, which is especially helpful in the context of picture classification, where there are frequently numerous potential features and classifiers to take into account.. Additionally, ACbGBM algorithms can be used to optimize the performance of ensemble classifiers, which combine the predictions of multiple base classifiers to improve accuracy. This has been shown to be an effective approach for leaf classification. In conclusion, by optimising the parameters of machine learning algorithms and ensemble classifiers, ant colony optimisation has been successfully applied to advance the state-of-the-art techniques for leaf classification, yielding a high degree of accuracy and performance.

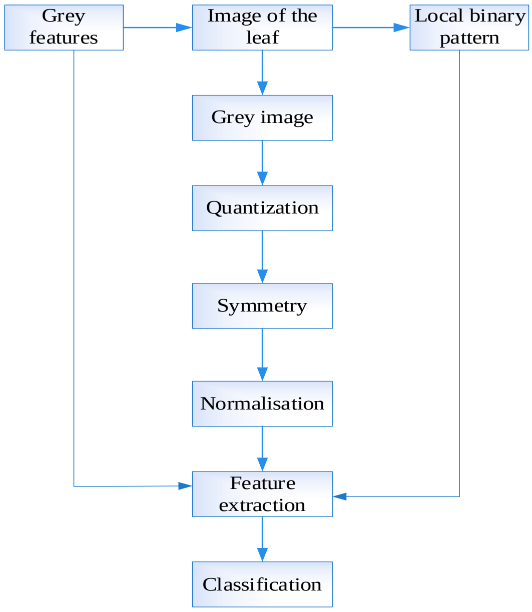


**Fig 4.** Workflow model of the proposed ACGBM for the herb leaves classification

**4.1 Proposed Design for ACbGBM**

Layers of the designed model are shown in Fig. 5. Five different layers were presented in the proposed model. The principal layer was the information layer at the information layer; informational collections were imported. The second layer was the hidden layer and Pre-processing was done there.

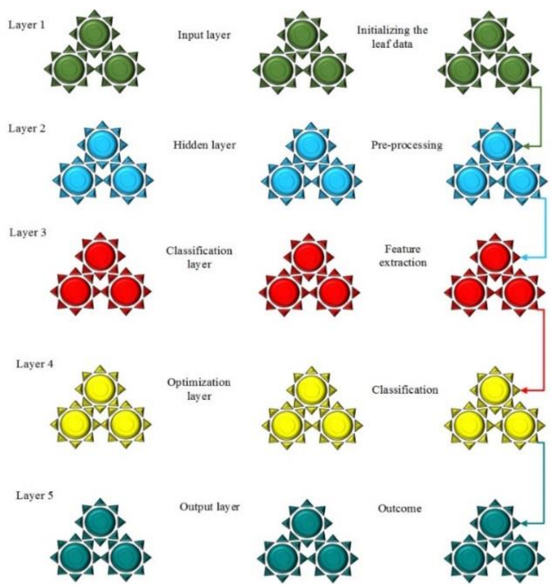


**Fig. 5** Layers of ACbGBM

In the classification layer, the third layer of the suggested model, features were extracted. After classification was completed over the optimisation layer, the fitness of the retrieved features was compared to the ant fitness. In addition, the last layer was the result layer. The resultant result was shown in the result layer.

**4.1.1 Pre-processing**

Before pre-handling at first, the spice leaves information was instated. In this exploration, leaf information was introduced. After importing the leaf data pre-processing was done. Here, the information introduction of the proposed model was communicated in eqn. (1),

$$\gamma(i) = \sum_{n}^{i=1}(l_1, l_2, l_3 \ldots\ldots\ldots\ldots\ldots\ldots l_n) \quad (1)$$

Where, $\gamma(i)$ was exactly the suggested model's initializing function worked, $l_1, 1_2, l_3 \ldots\ldots l_n$ determines the amount of data are included in the initial data set. Pre-processing was applied to the initialized data after data initialization. Besides, the instated dataset contains both clamor information along with silent information. Therefore, initially apply the kernel function using eqn.(2),

$$a(\tau) = p(\tau) * q(\tau) = \sum_{t=-\infty}^{+\infty} p(t)\, q(\tau - t) \quad (2)$$

Where, $p$ is denoted as initialized data, $q$ is represented as kernel function time then, the and time delay is denoted as $t$ and $\tau$ respectively. Then, the kernel function output is denoted using the eqn. (3),

$$n_i^{x,y} = \beta\left(e_j + m\sum_{r=1}^{m} f_r^{\,j} n_{i+s-1}^{x-1,y}\right) \quad (3)$$

Where, $n_i^{x,y}$ is represented as hidden layer output and linear mapping point is represented as $\beta$. For accurate results the noise data was removed from the initialized dataset. Pre-handling of the proposed model was communicated in eqn. (4),

$$\rho(p) = (I_1, I_2, I_3 \ldots\ldots I_n) - (I^*, I^{**}, I^{***} \ldots\ldots I^{n^*}) = \lambda_p \quad (4)$$

Here, $\rho(p)$ refers to the suggested model's pre-processing capability, $I_1, I_2, I_3 \ldots\ldots I_n$ refers to the noiseless data and $I^*, I^{**}, I^{***} \ldots\ldots I^{n^*}$ indicates the noise data in the set of data, $\lambda_p$ was considered as the noiseless data. Consequently, through pre-processing noise data were removed.

### 4.1.2 Feature Extraction

After feature extraction, the features that were not pertinent to the classification job were eliminated, and the pertinent features were extracted from the initial dataset. In this method, there are 10 layers, each of which has 10 features. The features are color, shape, texture features, length, Width, contrast, energy, homogeneity, entropy, and Correlation. The classification process was happening among the meaningful noiseless features for the purposes of this study, the components were separated based on the colour, size, area, and form of the leaves. Here, the first order feature extraction process is carried out by feature extraction method. This is mainly based on histogram behaviours of the collected images, so the first order feature extraction process contains skewness, mean and variance. Moreover, the mean ($\mu$) parameter represents dispersion size of an image and its calculated in following eqn.(5),

$$\mu = \sum_{m=0}^{M} g_m\, h(g_m) \quad (5)$$

Where, grayscale level of the ach collected image is denoted as $g_m$, $h(g_m)$ is represented as histogram value of the ach collected image. Furthermore, histogram value is incorporated with variance feature ($\sigma^2$) this can be calculated in following eqn. (6),

$$\sigma^2 = \sum_{m=0}^{M} (g_m - \mu)^2\, h(g_m) \quad (6)$$

Then, skewness that shows histogram curve and relative inclination level of an image. Consequently, skewness ($\alpha^3$) is calculated using the following equation: (7),

$$\alpha^3 = \frac{1}{\alpha^3}\sum_{m=0}^{M} (g_m - \mu)^3\, h(g_m) \quad (7)$$

However, the proposed model's feature extraction was expressed in equation (8).

$$\varphi = (I_1, I_2, I_3 \ldots\ldots I_n) - \omega l_n \quad (8)$$

At this research, $\varphi$ describing the proposed model's feature extraction function and $\omega l_n$ refers to the features that were taken from the pre-processed data. After extracting the features classification process was done over the extracted features.

### 4.1.3 Classification phase

Picture order was viewed as the focal issue in the current models. The properties of the suggested model were categorised according to the type of leaf in order to resolve the classification problems. In the classification phase, the extracted features of the initialized data set were classified. Here, 1000 images were chosen for processing. Among them, 300 were used for testing purposes, and 700 were used for training purposes. The images were classified based on the original label and predicted label function. Subsequently, the classification of the implemented design was declared in eqn. (9),

$$\lambda_c = if\begin{cases} Ol = Pl; & exact \quad classification \\ else \quad ; & wrong \quad classification \end{cases} \quad (9)$$

Where, $\lambda_c$ defines the model's classification function and $Ol$ relates to the initial label and $Pl$ defines the predicted label. Following classification, the implementation of the design presentation was approved. The parameters were measured in the form of Accuracy, error rate, precision, recall and f-measure.

Accordingly, the stream diagram of the executed plan was displayed in Fig. 6, and the functioning method of the planned model was created in pseudo-code design and was displayed in calculation 1. The proposed model's step-by-step function was described in the flow chart. The system was initially loaded using the leaf data set once it had been gathered. The noisy data was then removed using pre-processing. Then, feature extraction was completed. Meaningful features were extracted using the feature extraction features, whereas meaningless characteristics were ignored. After that, classification was done among the extracted features. Through the proposed model, a better type was obtained.

**Algorithm: 1 ACbGBM**

***start***

*{*

*Initialization*

int $\gamma(i), l_1, 1_2, l_3, l_n$

***Pre-processing is done by using eqn. (1)***

{

$\gamma(i) = \sum_{n}^{i=1}(l_1, l_2, l_3 \ldots\ldots\ldots\ldots\ldots\ldots l_n)$

}

***Feature extraction is performed by using eqn. (2)***

{

$$\varphi = (I_1, I_2, I_3 \ldots\ldots I_n) - \omega l_n$$

}

***Classification ()***

{

$if\ (Ol = Pl)$

{

***Exact classification***

}

{

***Else***

}

*Performance calculation*

***}***

***}***

***stop***

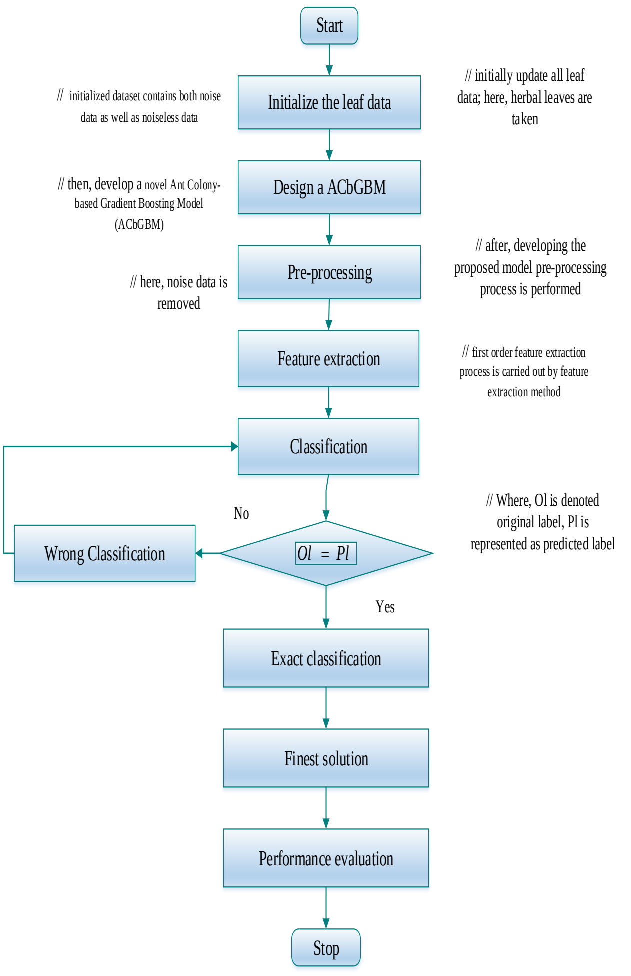


**Fig. 6** Flow chart

## 5 Result and Discussion

An optimized gradient boosting algorithm was developed in this article, which classifies the herbal leave typesThe presented work was created and tested using a dataset of herbal leaves. The presented model pre-process the dataset and extract the features for leaf specification. Further, the leaf features are trained to specify the herbal leaf type. The description of the parameters was listed in Table 1.

**Table 1** Parameter execution

| Parameters | Requirement |
|---|---|
| OS | Windows 10 |
| Version | R2020a |
| Platform | MATLAB |
| Data set | Herbal leaf data set |

Finally, the performances of the developed model are estimated by executing the developed model in the MATLAB software, version R2010a. Furthermore, the estimated results and system effectiveness are checked with a comparative analysis.

### 5.1 Case Study

The proposed model's working function was explained in detail in the case study. Initially, the herbal leaves data was collected and imported into the system. The proposed model was then created, and pre-processing was carried out using the proposed model The noise characteristics were subtracted from that. Then, at feature extraction, the better characteristics were extracted, and the undesirable parts were eliminated.. Moreover, leaf type classification was done based on the extracted features.

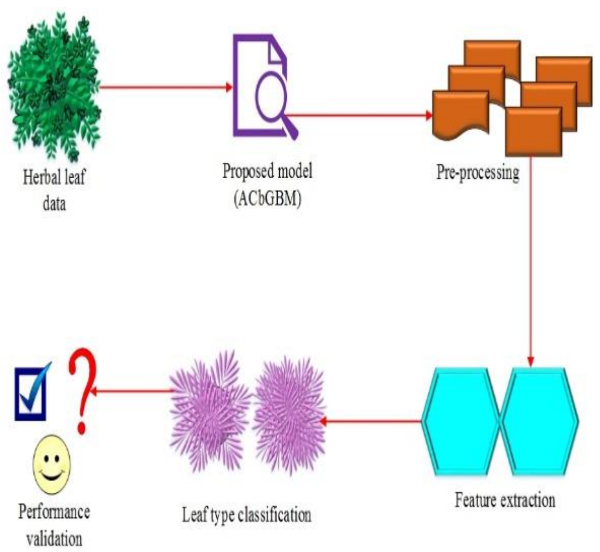


**Fig. 7** Work flow diagram of the proposed model

The presentation of the created model was therefore verified. Thus, Fig. 7 provides an illustration of the research's operational components. The present investigation was executed in the MATLAB platform through leaf data set. Providing better classification was the primary aim of this research. The fitness of the extracted features was compared with the ant fitness. After that extraction process was done. For this research, total of 1000 images were taken. Among them, 700 were used for training purposes, and 300 were used for testing. Figure 8 provides a few of the sample photos from the data set, and Figure 9 shows the experimental outcomes of the suggested model.

At first, the system was provided with some of the sample photos. After that, the system chose any one of the images randomly. Then if the predicted label and the original label were the same, the exact image was displayed.

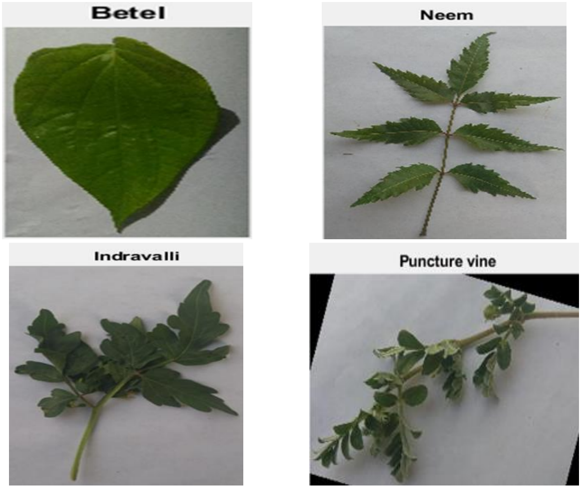


**Fig. 8** Sample images from the dataset

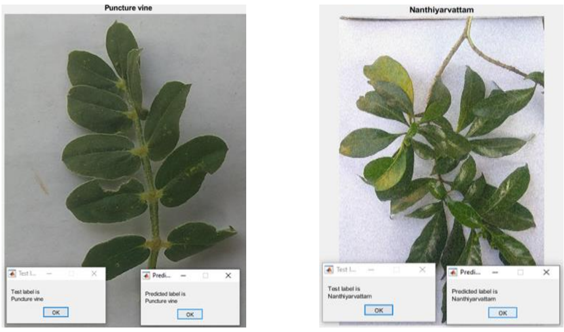


**Fig. 9** Experimental results

### 5.2 Performance & Comparison analysis

The performance investigation included a thorough discussion of the presentation of the implemented design. Accuracy, recall, precision, f-measure, and error rate were used in this section to validate the technique presentation that was put into practise. Through the proposed model, a higher performance rate was reached, indicating that the proposed model gives superior classification.. The suggested model (ACbGBM) was then put up against existing models like DL-based Morpho Algorithm (DL-MA) [41], vCrop [42], hybrid GCL model [43], and others to see how accurate, recallable, precise, and f-measure it was. The suggested model outperforms them all in terms of rate accuracy, f measure, recall, and precision, in addition to having a very low error rate.

#### 5.2.1 Accuracy

The rate of true positive, false positive, and true negative results, as well as a false negative, were used to gauge the suggested model's accuracyHere, a higher rate of accuracy indicates that the suggested model yields superior categorization outcomes. In this study, accuracy was determined by the categorization result. The accuracy of the proposed model was then expressed using equations (10),

$$\vartheta = \frac{\alpha + \beta}{\alpha + \alpha * + \beta + \beta *} \tag{10}$$

Where, $\vartheta$ denotes the accuracy calculating function of the proposed model, $\alpha$ defines the true positive rate, $\beta$ defines the rate of true negative, $\alpha *$ denotes the false positive with $\beta *$ refers to the false negative of the model. Also, the exactness pace of the planned model was contrasted with the current models to demonstrate that better precision was accomplished through the executed plan. The accuracy rate of the proposed model was around 99.677% which was high contrasted with the current models. The proposed model (ACbGBM) was contrasted with existing models like DL-MA, vCrop, hybrid GCL, and others to see how accurate it was. Among them, the suggested model acquired a higher accuracy rate, and Fig. 10 shows how accurate the proposed model compares to the others.

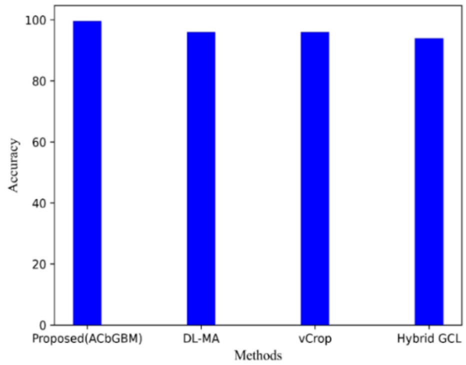


**Fig. 10** Accuracy comparison

#### 5.2.2 Recall

Based on the true positive and false negative rates, recall of the suggested model was evaluated. Increased accuracy raises the projected model's recall rate.. Additionally, the eqn (11), which was used to state the recall rate of the implemented design

$$\chi = \frac{\alpha}{\alpha + \beta *} \tag{11}$$

Here, $\chi$ describes the suggested model's recall function. When compared to other models, the implemented model's recall rate was high at roughly 99.81%.

The proposed model's recall rate was contrasted with that of the current models. Current models such as DL-MA, vCrop, hybrid GCL, and the suggested model (ACbGBM) were compared for recall rates the suggested model outperforms them all in terms of recall. Fig. 11 shows a recall comparison of the suggested model.

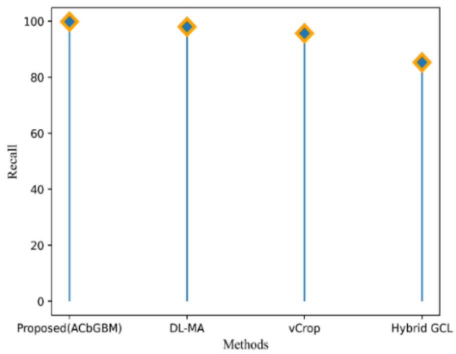


**Fig. 11** Recall comparison

#### 5.2.3 Precision

Based on false and true positive rates, the precision of the suggested model was determined. Further developed accuracy of the proposed model prompts giving a superior precision rate. Additionally, eqn. (12), which is the suggested model's recall rate,

$$\sigma = \frac{\alpha}{\alpha + \alpha *} \tag{12}$$

Where, $\sigma$ refers to the suggested design's exactness function. The precision rate of the carried out plan was around 99.355%, and the executed model's precision rate was contrasted with the current models.

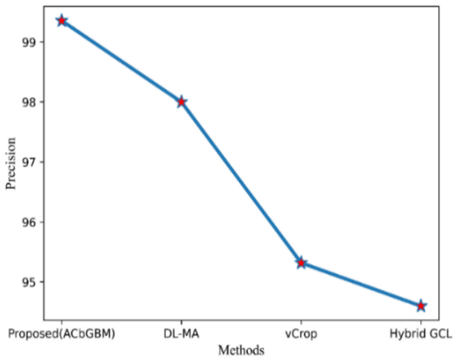


**Fig. 12** Precision comparison

Here the accuracy pace of the executed plan was contrasted with the current models like DL-Ma, vCrop, mixture GCL and the proposed model (ACbGBM). In examination, the proposed model achieved a superior precision rate. Consequently, the precision in comparison to the current models was displayed in Fig. 12.

***F-measure***

F-measure of the proposed model was estimated in view of the recall and precision rate. Expanded pace of recall and precision further developed the f-measure rate of the plan. Consequently, the f-measure rate of the executed strategy was communicated at eqn. (13),

$$f\_m = 2 \times \frac{\sigma \times \chi}{\sigma + \chi} \tag{13}$$

Where, $f\_m$ describes the function of the implemented design that calculates f-measures. Subsequently, the F-measure scope of the carried out model was around 99.889%, and the f-measure pace of the arranged model was contrasted with the current models.

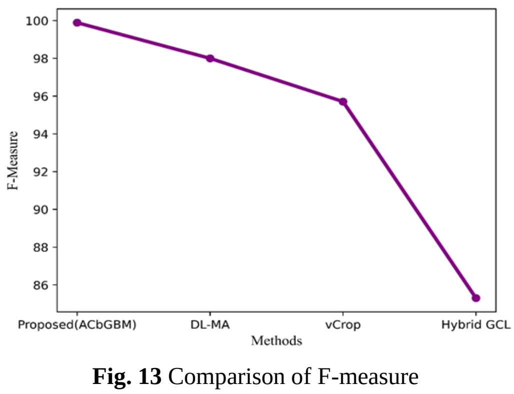


**Fig. 13** Comparison of F-measure

Here, the f-measure range was contrasted and the other existing models like DL-Mama, vCrop, half and half GCL and the proposed model (ACbGBM). In addition, the f-measure correlation of the plan was shown in Fig. 13.

The general examination of the proposed model is outlined in Table 2. There was a higher rate of boundaries achieved through the proposed model. After correlation, the arranged model's general show was talked about in the conversation area.

**Table 2.** Evaluation of planned model with other existing techniques

| Parameters | Proposed (ACbGBM) | DL-MA | vCrop | Hybrid GCL |
|---|---|---|---|---|
| Accuracy | 99.677% | 96% | 96.02% | 94% |
| Recall | 99.81% | 98% | 95.71% | 85.3% |
| Precision | 99.355% | 98% | 95.32% | 94.6% |
| F-measure | 99.889% | 98% | 95.51% | 95% |
| Error rate | 0.333% | - | - | 0.833 |

### 5.3 Runtime

The runtime of the ACbGBM will rely upon a few factors, for example, the size of the dataset, the quantity of choice trees in the GBM model, and the quantity of emphasess of the ACO calculation. In general, the runtime of the ACbGBM will be higher than other simpler models, such as a single decision tree, because it involves training multiple decision trees in an ensemble. The ACO algorithm also adds an additional computational overhead as it requires multiple iterations to converge to an optimal solution. Each iteration of the ACO algorithm involves updating the pheromone trails and calculating the probabilities of each feature to be selected. The increased classification accuracy of the ACbGBM model more than offsets this additional computational expense. However, it is anticipated that the ACbGBM will be competitive with other cutting-edge techniques that also include multiple decision trees and/or optimisation algorithms. Overall, the runtime of the ACbGBM will be longer than other simpler models. It is also worth noting that the runtime of the ACbGBM can be reduced by parallelizing the training process of the GBM model and the ACO algorithm. This can be achieved by distributing the training process across multiple cores or GPUs.

### 5. 4 Discussion

The discussion section calculates the overall parameters presentation of the planned representation.

Here, the precision rate of the developed model was about 99.355%, recall was about 99.81%, accuracy was about 99.677%, and a higher rate of f-measure was reached by the proposed model, which was about 99.889%. In any case, the proposed model accomplished a lower pace of blunder, generally 0.333%. In this manner, the expanded boundaries rate demonstrates that the proposed model was achieving better order results. In addition, Fig. 14 characterizes the general presentation of the proposed model

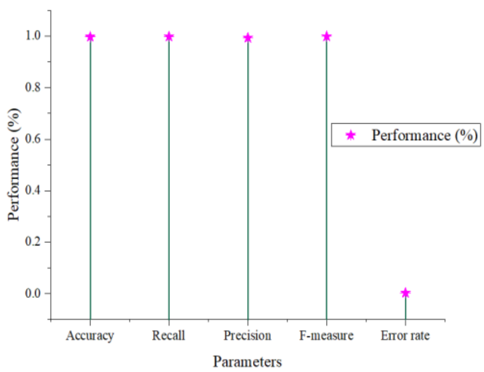


**Fig. 14** Overall performance of the proposed model

Then, the proposed dataset's accuracy was evaluated in comparison to those of Flavia [51], Trunk-12 [25], AFF [25], Soylultivar 200 [52], and Kaggle [53]. Here, Flavia has an accuracy of 95.3%, Trunk-12 has an accuracy of 86.76%, AFF has an accuracy of 82.93%, Soylultivar 200 has an accuracy of

83.55%, and Kaggle has an accuracy of 96.89%. But, the proposed datasets has attained 99.677% accuracy, which is higher than the other datasets.

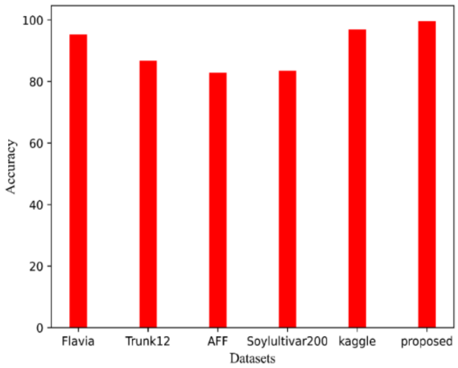


**Fig. 15.** Dataset comparison

## 6 Conclusion

This present investigation was about detecting the type of leaves based on the classification result. For this initiative, the leaf data was collected and imported into the system, and then the noise data were removed through the pre-processing mechanism. Additionally, include extraction was finished here. The trivial elements were eliminated from the informational collection, and the full importance highlights were picked for additional grouping. Through the proposed model higher pace of boundaries was achieved. This demonstrates that the proposed model gives better order. The precision of the plan was around 99.677% contrasted and other existing models, and the accuracy rate of the proposed model expanded by 1%. The recall score of the created model was around 99.81% contrasted and different models; 9% of recall was worked on in the proposed model. Consequently, the precision rate of the carried out plan was 99.355% contrasted with the current models; 8% of the precision rate was made do in the executed strategy. In addition, the f-measure pace of the planned model was around 99.889%; through the proposed model, 9% of the f-measure rate is moved along. The lower error rate accomplished through the proposed model was generally 0.333%. In this way lower error rate was accomplished through the proposed model, demonstrating that the proposed model gave the best characterization results.


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None


### Compliance with Ethical Standards

1. Disclosure of Potential Conflict of Interest:

The authors declare that they have no potential conflict of interest.

2. Statement of Animal and Human Rights

*i.Ethical Approval*

All applicable institutional and/or national guidelines for the care and use of animals were followed.

*ii.Informed Consent*

For this type of analysis formal consent is not needed.

### Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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