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TRACING AND RECOGNITION OF MEDICINAL HERBS IN MARUNTHUVAZH MALAI AT THE WESTERN GHATS THROUGH FEATURE EXTRACTION

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Abstract

The identification and classification of the herbs using the naked eye is difficult in forest or mountain areas like Marunthuvazh Malai of Kanyakumari district. The difficulties arise because of the variations in the crops identified are inaccurate. Mostly the manual prediction is taken place in those areas which require high expertise and more human resources. In this work both plant identification and tracking system based on fuzzy empowered Hybrid artificial neural networks (FHANN) are proposed. Here the input is taken from the video signals taken by the drone camera. The input video signals are converted into images. The fuzzy logic along with the HANN is used for the classification of the specific herbs from the set of plants. Some of the herbs included in the analysis are Parsley, Dill, Oregano, Chervil, Stevia, Basil, Catnip, Fennel and Lemon Grass. This approach used artificial neural networks (ANN) in combination with the K-Nearest neighbor (KNN) as the hybrid model for the herb prediction and classification in association with the fuzzy logic. The Linear Discriminant Analysis (LDA) and Convolutional Autoencoder are used as a hybrid model for the extraction of the feature from the obtained images. This approach considers various shapes, color features, and textures specifically representing the specific herbs. The experimental results show that the proposed model provides better results in the identification and classification of the various medicinal herbs.

Keywords:

Herbs, Artificial Neural Networks, K-nearest Neighbour, Linear Discriminant Analysis, Convolutional Auto encoder

1. INTRODUCTION

The foundation for Traditional Chinese Medicine (TCM), which aims to maintain and improve human health, is derived from a diverse range of plants used for medicinal purposes [1]. The basis for preserving and enhancing human health need to be preserved and to be authenticated. Traditional Chinese Medicine needs to be taught how to identify different types of TCM; consequently, the investigation and application of medicinal plant classification methodology is essential [2]. Traditional Chinese Medicine is currently being researched and put into practice in China. This branch of Medicine has a rich history in China and has made significant advancements in human health and the treatment of disease [3]. Most of the components that make up TCM, such as phytomedicine, animal medicine, mineral Medicine, and others, are derived from natural materials and the by-products of these components. The term complementary medicine can also be used to refer to Traditional Chinese Medicine [4]. Traditional Chinese Medicine in China consists of 12,807 distinct types, with phytomedicine accounting for more than 87% of the total [5]-[6].

Because China has an abundance of natural resources, the country can produce a significant amount of TCM. Because there are so many distinct kinds of medicinal plants and the qualities of those plants can change depending on where they are grown, the terms homonym and synonym were invented to describe this phenomenon. Homonyms and synonyms are used interchangeably to refer to the same thing. Even in the present day, there are still many instances of people confusing TCM varieties with one another. This is because the location of the medication, its appearance, and its name are all very similar. In 2022, kidney failure and urethral cancer were observed in Hong Kong patients who had taken Chinese Medicine because Solanum lyratum Thunb was substituted for Aristolochia mollissima Hance [7]. As a direct result of the concept of health care, there has been an increase in the number of people seeking natural medicines. This increase has occurred concurrently with the expansion of both the economy and the medical industry [8].

The industry of Chinese Medicine has been driven to an excessive pursuit of profit, which has resulted in an overexploitation of the available resources [9]. The ongoing destruction of the natural environment is putting a significant number of valuable medicinal plants in danger of going extinct. This is since the natural environment is being degraded. The market for traditional Chinese Medicine is flooded with products of dubious authenticity and poor quality because of an imbalance between supply and demand. The development of environmentally friendly practises and the state of human health have been significantly hampered as a direct result of the negative impact of these issues [10]-[12].

Traditional Chinese medicine authentication, the protection of the resources used in traditional Chinese Medicine, and the categorization of medicinal plants have become active research areas. Identification of medicinal plants is almost always done by hand. In the beginning, the plant is analysed using the eyes, nose, hands, and other human organs available to determine its shape, colour, flavour, and consistency [13]. This process can be carried out on a specific plant section or on the entire plant (leaf, flower, fruit, or bark).

After that, the species of medicinal plants are characterised with references or through direct observation, whichever comes first. On the other hand, this identification method has been shown to be inefficient, time-consuming, and highly dependent on the individual prior knowledge and experience. This was shown through actual application. This is since the method depends on the expertise and knowledge of the individuals involved in the process. In recent years, there has been a rise in the prevalence of computer-based automatic image recognition because of advancements in closely related technologies such as image processing and pattern recognition. This has led to an increase in the use of computer-based automatic image recognition.

In addition to this, computers are getting better at recognising complex patterns [14]-[15]. The creation of a classification system for different types of medicinal plants. The application of this methodology has significant repercussions for both the automatic classification of medicinal plants and the utilisation of computers as educational aids. A great number of seasoned professionals and academics have carried out extensive research in the fields of plant leaf image processing and recognition, which has resulted in fascinating discoveries.

2. LITERATURE SURVEY

The most important aspects of image recognition are feature extraction and classifier selection, which are two of the many components that make up image recognition. These variables will directly impact the results of the process of leaf image recognition due to the immediate impact they will have. Using the Move Median Center (MMC) hypersphere classifier in conjunction with the eight geometric features and seven invariant moment features that were extracted from plant leaf images by Kan et al. [16], the researchers were able to classify twenty distinct plant leaf species. Ping and colleagues were able to generate an image of the plant leaves by utilising invariant moments. A recognition rate of 92 percent was accomplished by classifying the image with artificial neural network (ANN) assistance. This activity is now considered finished. Kalyoncu et al. [17] modified the Multi-scale Distance Matrix, also known as MDM, and the average margin distance so that they could provide a better description of the leaf margin.

In addition, it has been reported that utilising a technique that uses a complex network to investigate the form of the plant leaf boundary can produce results that are to the investigator satisfaction. Support vector machine (SVM) and the random forest (RF) method were proposed as a possible combination by Sachar et al. to classify plant leaves [18]. The form and coloration of the leaf were the most important characteristics by Sachar classification system, which was based on the leaf. The image of the leaf was given a classification by using the 1-KNN algorithm in accordance with the supervised locality projection analysis (SLPA) that was proposed in [19] [16]. In addition, the texture of plant leaf images is often utilised to classify and group plant species.

Identification of plant species using computer technology has had a significant influence on the plant digital museum system as well as systematic botany, both of which are essential foundations for the development of future plant research and development. This work presents a novel approach to the identification of plant species using photographs of the leaves of the plants. It places an emphasis on the extraction of stable leaf features, such as the geometrical features of shape and the textural features of venation, among other such features [20]. It is possible to determine the species of a plant based solely on its leaf since each leaf has its own distinct shape, size, and organisation. By analysing the prominent characteristics of the leaf, the technology known as Computer-Aided Plant Species Identification can correctly identify known plant species. The system primary objective is to identify the fixed characteristics of plant species that can be used to differentiate them from the fixed characteristics of other species. This can be accomplished by comparing plant species fixed characteristics to other specie fixed characteristics [21].

Previous research has primarily concentrated on identifying leaves based on their shape, ignoring the venation of the leaf, which contains crucial information about the leaf texture [22]. This is because the venation of the leaf contains information about the leaf veins. This is because the venation of the leaf contains important information. During this study, the geometrical and textural characteristics of plant specimens are examined in order to determine the species conclusively. Without agriculture, the Philippine economy would not be able to function. Bananas, pineapples, and mangoes have all worked their way up to the top of the list of essential crops because of the large amounts of food they have been able to sell overseas.

On the country local markets, where it has become well-established, the mango is currently ranked third in terms of its popularity. Even more fortunately, there is a good possibility that this harvest will be offered for sale on international markets, either in its natural state or after undergoing a significant amount of processing. This may include goods that have recently been harvested or products that have been manufactured. The Carabao mango that is native to this country is widely considered to be among the best examples of its kind anywhere in the world. In addition, a wide variety of mango subspecies are grown commercially in this country. Individual family farmers own seventy-three percent of the land that is planted with mango trees, while farm-operating businessmen have ownership of twenty-four percent of the land. The sizes of these farms range between three hundred and three hundred fifty hectares each. It is estimated that approximately 2.5 million mangoes are shipped out of the country each year, providing a significant portion of the agricultural workforce with a means of subsistence.

Approximately 70% of the total sales made in the country are considered to be domestic sales. Making an educated guess about the type of plant that produced a particular crop based solely on appearance can be challenging and is not guaranteed to be correct in all cases [23]. This is correct because one should not place too much stock in first impressions. Botanists are the only professionals who are qualified to perform this task, and it takes a considerable amount of time to differentiate between the different kinds accurately [24].

Digital image recognition has quickly become one of the most important applications for industrial systems in recent years; this is done in order to save users time and make their lives easier. In spite of the fact that these techniques have been around for quite some time, there is still room for improvement in order to achieve the level of efficacy and precision that is desired. In recent years, many research projects have been finished to develop models for the analysis of plant leaves, improving existing models, and computerising them [25]. The previous studies utilised shape recognition to create models and representations of the leaf contour. In addition, Binary and RST-Invariant features were compiled in an effort to achieve a higher level of recognition precision [26]. Banhawy et al. [27] proposed a method for identifying mango varieties that was based on the geometrical and morphological characteristics of the leaves that are found on mango trees. This technique is predicated on the idea that different varieties of mango each possess a unique combination of geometrical and morphological characteristics. Singh et al. [28] at their company developed a method for identifying weeds based on image processing and PNN. One of the many subtypes of many-valued logic is called fuzzy logic.

There are many other subtypes as well. As a result of this range, the validity of the variables is determined; consequently, the term fuzzy logic was coined. In contrast to this, the truth value of a factor is simply the 0 or 1 qualities that are utilised in Boolean logic to represent the concept of partial truth. According to this line of reasoning, the value 0 and the value 1 are respectively either entirely true or entirely false, whereas the value 1 may be either entirely true or partially true. This is because in Boolean logic, the values 0 and 1 can either be correct or incorrect. The application of fuzzy logic is something that humans are very good at and find very natural. A fuzzy set does not allow for the precise definition of any boundaries because the membership function of a fuzzy set is more generalised than the membership function of a standard set, which has limits that are predetermined [29].

On the other hand, a standard set has predetermined limits. This is because it is impossible to define boundaries with exactitude. A rule-based framework that, depending on the level of functional experience of the operator, may rely on standard rules is the most fundamental form that the fuzzy rationale can take. This form can be reduced to its most basic form by following these steps. The operator prior knowledge can be captured more effectively with the help of this framework. K Nearest Neighbor, also known as KNN, is one of the simplest and most fundamental classification techniques. The KNN technique should be among the first options for characterising the data when there is limited prior knowledge about the distribution of the data, and when there is limited prior knowledge about the distribution of the data, it should also be among the first options [30]. The KNN technique requires the use of a non-parametric classification technique, which completely sidesteps the issue of probability density.

The KNN technique also requires that you use a non-parametric clustering technique. The primary goal of this scheme is to organise an input query, denoted by the letter x, into the label that comes after it in the order of the labels that are immediately adjacent to it. This suggests that the classification of the input is decided upon by comparing the values of the input to those of the data and selecting the value that is the most comparable to those of the data. According to the KNN rule, x is the instance that occurs more frequently than any of the K instances that are the closest together. This research aims to categorise the numerous varieties of mango based on the image processing techniques used to examine their morphological characteristics. It should be used as one of the sets of input parameters for fuzzy logic as well as k-NN, and then the results should be compared.

3. PROPOSED APPROACH

In this work, herbs classification and identification systems are proposed for distinguishing the various species of herbs in the captured video inputs taken from Marunthuvazh Malai of Kanyakumari district which is carried out by a UAV (Unmanned Aerial Vehicle). The taken videos are converted into video frames and then to images. The obtained images are subjected to a Kalman filter for noise removal and after removing the noise it is then sent to a hybrid model LDAC comprised of Linear Discriminant Analysis (LDA) and convolutional auto encoder for extracting the features in order to identify the features. The features considered here are Branching Patterns, petals count, leaf shape, and habitat. After extracting the features, it is then exposed to Fuzzy-based hybrid Artificial neural networks (FHANN) which takes on the combination of KNN and ANN in coordination with fuzzy logic for the classification and prediction of various herbs that get existed in Marunthuvazh Malai. The overall architecture is illustrated in Fig.1.

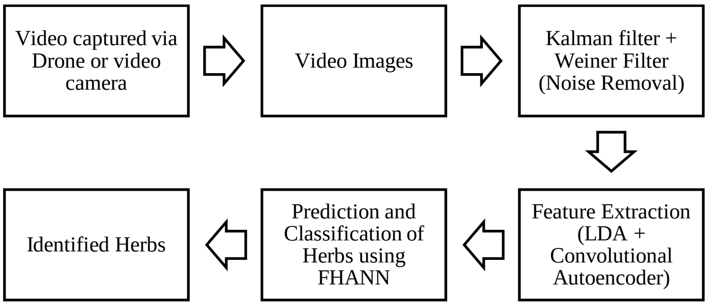

Fig.1. Architecture of Proposed System

3.1 IMAGE ACQUISITION

The acquiring of the images can be made by means of a drone or digital camera. The drone or UAV system might capture the video from all areas of the hills. The captured videos are stored in a database for testing purposes, specifically the real-time videos. But for training purposes alone we are taking the pre-stored data which is stored in a predefined directory. Some of the sample images stored in the directory are shown in Fig.2.

Fig.2. Sample Images for Various Herbs Considered in this Approach

From the set of images taken from the Hills, some of the frequent medicinal value herbs are taken as samples from the directory. The identification of the herbs from the total set of databases is done with the help of various image acquisition techniques. Mostly the drones or the UAV might contain the inbuilt cameras for capturing the images and the videos from the unapproachable terrain like Hills. Based on the quality of the camera and its general features the capturing of the videos or the images can be done in any terrain in different environmental conditions like sunny, dark, cloudy, and rainy. Mostly, drones are used here, as it may fly over the terrain for capturing the videos or images. The movable platform setup is installed with onboard sensors for approaching and monitoring the different types of medicinal herbs.

3.2 PRE-PROCESSING THE CAPTURED IMAGES

The obtained images are to be converted into suitable format for making it comfortable to fit into the algorithm for training and testing purposes. The obtained video frames might be of different size and the pixel range may also get varied. Hence suitable pre-processing technique is needed. The obtained image from the video is cropped and the sizes of the images can be converted into fixed sizes and hence it is made easily available for testing. It may accompany with suitable digital image processing techniques to match up with the computerised algorithms used. Some of the pre-processing steps involved here in this approach is the change of size of the image (into fixed size), Image segmentation, cropping and binarization. Here K-Means segmentation process is used for arranging the similar pixels of the image.

3.3 HYBRID WK (WIENER +KALMAN) FILTER FOR NOISE REMOVAL

The removal of noise is the most important part in this approach. The video signals are converted into frames and the frames are then converted into images. Hence the image might contain some noises which should be removed for further processing. The implication of the Kalman filter made in association with the Wiener filter may corresponds to the dual estimation related issues. By using the Kalman filter and the Wiener filter the various methods for performing the noise removal is made in an efficient manner. Each time points may correspond to the optimal filtering which includes the combination of both filtering process in hybrid manner.

The WK filter filters the noisy signal by using the properties of the spectrum in correlation with the expected noise signal. This will remove the noises by considering the stochastic process along with the linear property. Here the temptation of the linear filter is implied along with the coefficients K_w after estimating the signal. The input signal, α(n) consists of the noise ε(n),

$$\alpha(n) = r(n) + \varepsilon(n) \tag{1}$$

The signal predicted at the output y(n) might be considered close to the estimate r(n). Hence the error signal ε(n) might be set to minimum. The adaptive algorithm will try to correct the corresponding weights K_w, hence the mean square error may be reduced and it is mathematically expressed as

$$\varepsilon = \min(E(\varepsilon(n)^2)) \tag{2}$$

Here,

$$\varepsilon(n) = \alpha(n) - r(n) \tag{3}$$

For obtaining the value of y(n) the WK filter uses the following mathematical expression

$$y(n) = \sum_{k=0}^{N-1} K_w (d(n-k) * \varepsilon(n-k) \tag{4}$$

The wiener-Hopf equation is used for calculating the weights and it is expressed mathematically as

$$\sum_{i=0}^{\rho-1}\sum_{j=0}^{\eta-1} K_{xy}\gamma_{xy}(k-1) = \Gamma_{xy}(i,j) \tag{5}$$

Each value of K_{xy} may correspond to the tap weights of the filter and $\Gamma_{xy}(i,j)$ is considered as the autocorrelation function of input $x(n)$. The WK filter used here uses stochastic measurements. It is mathematically expressed as

$$\sum_{k=1}^{n} \hat{\alpha}(k+1) \,||\, k = \mathrm{X}.\Delta\hat{\alpha}(k) + \mathrm{X}.\Delta\hat{\alpha}(k)\mathrm{X}^T + K_w.\Delta \tag{6}$$

Then the gain of K_w is obtained as

$$K_{w(k+1)} = \sum_{k=1}^{n}(k+1) \,||\, k\left[\mathrm{H}_k \sum_{ij} H^T + V_{ij}\right] \tag{7}$$

Here the standard K_w filter may be adequate while the trajectory phenomenon is confined to a single domain to process hybrid events. The algorithm used for the representation of the WK filter is given below in algorithm 1.

Algorithm 1: Hybrid KW filter

$Input\ \left(A_k, B_k, X_{k,} Y_k, Z_k\right)$

$\hat{a} \leftarrow A_k, \hat{b} \leftarrow B_k, \hat{x} \leftarrow X_{k,} \hat{y} \leftarrow Y_k$

while $(\hat{a} < A_k + \Delta) do$

$(\hat{a}, \hat{b}) \leftarrow \text{integrate}\, \Gamma_1(\hat{a}, \hat{b})$

$\text{until}\, (\hat{a} = a_k + \Delta)\, \text{or}\, (\Sigma j \,||\, a \in R(i,j)$

$\Delta \leftarrow \hat{a}^+ - a, \hat{a} \leftarrow \hat{a}^+$

$A_k \leftarrow \mathrm{K}_w.\Delta_1 \sum_{ij} A(i,j).\Delta_1 + K_{w.\Delta 1}$

$B_k \leftarrow \mathrm{K}_w.\Delta_1 \sum_{ij} B(i,j).\Delta_1 + \sum K_{w.\Delta_1}$

$X_k \leftarrow \mathrm{K}_w.\Delta_2 \sum_{ij} X(i,j).\Delta_2 + K_w.\Delta_2(R)$

$Y_k \leftarrow \mathrm{K}_w.\Delta_2 \sum_{ij} Y(i,j).\Delta_2 + K_w$

if $\Gamma \in R(i,j)$ then

$\hat{a} \leftarrow G(i,j)(\hat{a}, \hat{b})$

$\hat{b} \leftarrow \sum_{ij} K_w.\Delta + K_{w(i,j)}$

end if

end while

$M \xleftarrow{k=1} \sum C^T{}_k.\Delta_v \left[C_k \sum C_{ij} + R_1\right]^{-1}$

$\hat{a} \leftarrow \hat{a} + K_w\left[Z_k - C_1.\hat{a}\right]$

$\hat{b} \leftarrow \hat{b} + K_w C_1.\hat{b}$

if $\hat{b} \in G(i,j)$ then

$\hat{b} \leftarrow R(i,j)(\hat{a}, \hat{b})$

end if

$a_{k+1} \leftarrow \hat{a}, b_{k+1} \leftarrow \hat{b}, x_{k+1} \leftarrow \hat{x}, y_{k+1} \leftarrow \hat{y}$

$return\left(a_{k+1}, b_{k+1}, x_{k+1}, y_{k+1}\right)$

3.4 FEATURE EXTRACTION USING HYBRID MODEL LDAC

The hybrid model LDAC comprised of Linear Discriminant Analysis (LDA) and convolutional auto encoder. This is for the reduction of dimension and feature extraction. It is widely used in major applications like high dimensional data like image retrieval. Here in this approach, the 2-Dimensional Linear Discriminant Analysis is the proposed in this work. The 2-D LDA uses data along with matrix representation.

The 2-D LDA uses the representation ($\rho_1 \times \rho_2$) under the dimensional space $R \times L$. This could be the tensor product of the two spaces R and L, where R is spanned by $\{u_i\}^{r_1}_{r_i=1}$ and the L is represented by $\{v_i\}^{r_2}_{r_i=1}$. Here the two matrices are mentioned as $R = [u_1, u_2, \dots u_n] \in \mathbb{Z}^{rxu_1}$ $L = [v_1, v_2, \dots v_n] \in \mathbb{Z}^{cxv_1}$. Here the optical transformations sensed in L and R is preserved in two-dimensional space. The metrices are used for the representation of the matrices within the class and in between the classes to occupy with the distance D_x and D_y, which could be calculated as below:

$$D_x = \sum_{i=1}^{m} \sum_{X \in \Phi} \| X - Y \|^2 \tag{8}$$

And

$$D_y = \sum_{i=1}^{n} \sum_{\omega \in \theta} R_n \| Y - X \|^2 \tag{9}$$

By using the trace property, the value of (RR^T)=$\|R\|^2$.But for other matrices the expression can be rewritten as

$$D_x = trace\left(\sum_{i=1}^{m} \sum_{X \in \Phi} | (X - Y)(X - Y)^T \right) \tag{10}$$

and

$$D_y = trace\left(\sum_{i=1}^{n} \sum_{\omega \in \theta} R_n \left(X - Y_m \right)\left(Y_m - X \right) \right) \tag{11}$$

Considering the original video input, the obtained image might be in either one-dimensional or in two -dimensional form where the new representation might belong to the predicted m-dimensional space. Here the auto encoder is used in the three-layered neural network with the support of back propagation algorithm which is used for training. Which could be represented as

$$\psi_{x,y} = \chi(f(x)) \approx x \tag{12}$$

$$\lambda(W, x : a, b) = \frac{1}{2} \| \Psi_{x,y}(\alpha) - y \|^2 \tag{13}$$

Considerably the low-dimensional space might get the optimal transformations in R and L that could increase the values of D_x and D_y. The computation of R and L is very difficult, specifically for the fixed values of R. The value of L can be computed using the expression.

$$\left.\begin{aligned} D_x &= trace(R^T \mathrm{N}^R{}_x L_n) \\ D_y &= trace(R^T \mathrm{N}^R{}_b L_m) \end{aligned}\right\} \tag{14}$$

And the value of R can be calculated using the formula:

$$\left.\begin{aligned} D_x &= trace(R^T \mathrm{N}^R{}_x R_n) \\ D_y &= trace(R^T \mathrm{N}^R{}_b R_m) \end{aligned}\right\} \tag{15}$$

The algorithm for Feature Extraction using hybrid model LDAC is shown in algorithm 2.

Algorithm 2: Procedure for LDAC

Algorithm: $2DLDA(D_1, D_2, \dots D_n, L_1, L_2)$.

Input: $D_1, D_2, \dots D_n, L_1, L_2$.

Output: $L, R, \mathrm{E}_1, \dots, \mathrm{E}_n$.

Compute the mean X_i of i^{th} class for each i as $X_i = \frac{1}{n_1} \sum_{x\hat{\imath}\Pi} X$

Compute the global mean $X_i = \frac{1}{n} \sum_{x\hat{\imath}\Pi} X$

$R_o \leftarrow (Il_2, 0)^T$;

For j from 1 to l

$\Psi_x{}^R \leftarrow \sum_{i=1}^{k} \sum_{X \in \Pi} \left(X - Y_m \right) R_{i-1} \left(X - Y_i \right)$

$\Psi_y{}^R \leftarrow \sum_{i=1}^{k} \sum_{X \in \Pi} \left(X_1 - Y_N \right) R_{i-1} \left(X_2 - Y_N \right)$

Compute the l value

$L_j \leftarrow \left[\varphi_1, \dots \varphi_n \right]$

$\Psi_y{}^R \leftarrow \sum_{i=1}^{k} \sum_{X \in \Pi} \left(X_1 - Y_N \right)^T R_{i-1} \left(X_2 - Y_N \right)^T$

$R_k \leftarrow \left[\varphi^r{}_1, \dots \varphi^r{}_n \right]$

End For

Return$(L, R, \mathrm{E}_1, \dots, \mathrm{E}_n)$

4. FUZZY EMPOWERED HYBRID ARTIFICIAL NEURAL NETWORKS (FHANN)

The FHANN is implemented with the combination of artificial neural networks (ANN) and k-nearest neighbor (KNN). The KNN was implemented because of its simplicity and efficiency. The subject samples are explained with the consideration of the numerical n-dimensional features. The number of samples is projected in case of these features for further dimensions. Hence all the subject samples are indicated with n-dimensional features.

The neural networks are considered as one of the members in the parametric techniques and non-parametric methods which might be used for further classification and estimation. The application of ANN is more capable in recognizing the patterns using most appropriate tools for classification. Considering the previous classification methods, the ANN provides the better way in classifying the contents in appropriate manner.

The ANN is initially developed based on the consideration of the human nervous system that incorporates the neurons. The relation between the systems may determine the overall network behaviour and hence the selection of the network type might be solved depending on the issues considered. The architecture of the ANN is shown in Fig.2.

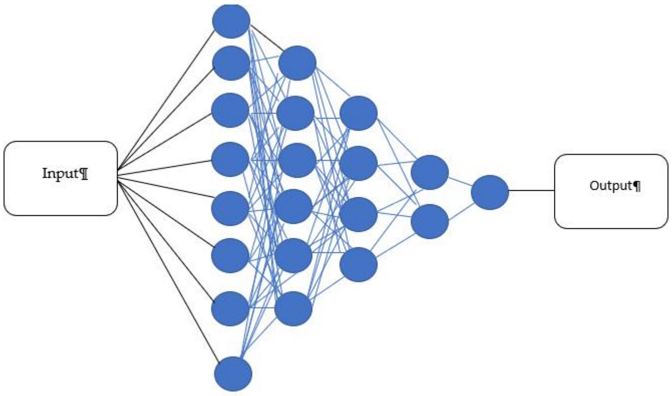

Fig.3. Neuron Model based on ANN and KNN

Mostly the back propagation networks are used which can use the potential data. This setup is formulated using the network learning mechanisms. The combination of the KNN along with ANN initiates the feed forward learning process with the help of back propagation algorithm. The main advantages of this FHANN network are the usage of the potential data for determining the weights. The classification is done with proper estimation techniques. The ANN is acting most appropriate to the other classification methods. The algorithm corresponds to the FHANN algorithm is shown in algorithm 3.

Algorithm 3: Procedure for FHANN

Begin

Initializing the parameters(a,x,y,b,z)

Blogger={Parsley, Dill, Oregano, Chervil, Stevia, Basil, Catnip, Fennel and Lemon Grass}

New blogger={Parsley+1, Dill+1, Oregano+1, Chervil+1, Stevia+1, Basil+1, Catnip+1, Fennel+1 and Lemon Grass+1}

Function classification:

For each blogger do

Shape: shape of the leaf, petals etc.

Color: color of the leaf, stem etc.

Texture: Leaf texture

End

Function Identification:

For each iteration do

I_1: Parsley

I_2: Dill

I_3: Oregano

I_4: Chervil

I_5: Stevia

I_6: Basil

I_7: Catnip

I_8: Fennel

I_9: Lemon Grass

End

End

5. RESULTS AND DISCUSSION

The video signals are captured using the drone or UAV or digital camera. Here we use DJI Mavic Mini 2 Bundle Fly More Combo Drone With 4K Video Recording and the system used for processing is having i3 processor (11th generation) with 8GB memory space. The software used here is python version 3.9.7. The images of groups of plants are captured as video signals and after processing it some of the features are identified like colour, shape and textures. Totally 8 different herbs are considered. The images captured from video signals are 110 in count. From the 110 captured images these 8 various herbs are notified using certain features. The KNN and ANN are combined together in analysing the features. Some of the samples are shown in Fig.4.

Fig.4. Sample Leaves taken for training purpose

These images are taken from the selected frames. The images are pre-processed at the beginning stage and the features are extracted by using certain methodologies by keeping track of certain mathematical expressions. The parameters considered here is compactness, eccentricity and aspect ratio for estimating the shape features. Then mean, standard deviation, skewness and kurtosis for estimating the color features. Then the texture features are calculated using Energy (E), Contrast (Cont), Correlation (Cor), Inverse Difference Movement (IDM), Sum of Variances (SOV), Average sum (AS), Entropy (En), Difference Entropy (DE) and Sum Entropy (SE). The Estimated values for the determination of the shape features of the Herbs are shown in Table.1.

The average value obtained in estimating the shape features is marked as 0.7018 for Eccentricity, 1.05866 for Compactness, 1.4155 for Aspect ratio. Some of the other parameters like rectangularity and circularity are also determined for the estimation of the shapes of the Herbs. The rectangularity may possess the average value as 0.3568 and the circularity might posses with the average value 24.15. The obtained average values of various shape determining parameters are illustrated in Table.1.

Despite shape features the texture might play a key role in identification of the herbs. The texture may correspond to certain values determined under the labels Energy, Entropy, contrast, correlation etc is shown in Table.2.

Table.1. Parameters for Estimating the Shape Features

Sl. No	Eccentricity	Compactness	Aspect Ratio	Rectangularity.	Circularity
1	0.675	1.005	1.335	0.33	29.573
2	0.703	1.061	1.419	0.358	19.996
3	0.756	1.167	1.578	0.411	19.25
4	0.567	0.789	1.011	0.222	37.521
5	0.654	0.963	1.272	0.309	19.323
6	0.665	0.985	1.305	0.32	18.658
7	0.684	1.023	1.362	0.339	29.566
8	0.64	0.935	1.23	0.295	22.809
9	0.726	1.107	1.488	0.381	23.446
10	0.775	1.205	1.635	0.43	18.629
11	0.823	1.301	1.779	0.478	27.742
12	0.754	1.163	1.572	0.409	23.365
Average	0.702	1.059	1.416	0.357	24.157

Table.2. Parameters for Estimating the Texture Features

Sl.No	Energy	Entropy	Contrast	Correlation	Inversion	Sum of variances	Average sum	Sum entropy	Difference entropy
1	1.52E-02	7.72E-03	6.07E-02	2.04E-05	1.33E-02	0.37812	0.37874	4.94E-01	-4.78E-01
2	1.75 E-02	4.86E-01	4.28E-02	2.47E-05	1.57E-02	0.376765	9.73E-01	-1.24E-03	-1.24E-03
3	1.58E-02	4.87E-03	4.63E-02	3.07E-05	1.39E-02	0.37417	0.37683	9.70E-01	5.19E-03
4	1.51E-02	4.82E-03	4.89E-02	1.16E-05	1.32E-02	0.37949	0.38445	9.70E-01	-5.32E-03
5	1.65E-02	4.87E-03	4.65E-02	2.22E-05	1.47E-02	0.38941	0.38542	9.85E-01	-9.92E-03
6	1.50E-02	4.97E-03	5.13E-02	1.89E-05	1.31E-02	0.38143	0.38394	9.87E-01	7.98E-03
7	1.52E-02	4.89E-01	4.80E-02	1.68E-05	1.33E-02	0.38645	0.38224	9.84E-01	-5.02E-03
8	1.86E-02	4.94 E-01	6.73 E-02	2.56 E-05	1.73 E-02	0.37803	0.3757	9.80 E-01	8.42E-03
9	1.67E-02	4.86 E-01	3.59 E-02	2.47 E-05	1.48 E-02	0.37337	0.374515	9.67 E-01	4.66E-03
10	1.78E-02	4.81 E-01	3.17 E-02	1.96 E-05	1.61 E-02	0.37566	0.321575	9.65 E-01	-2.29E-03
11	1.54E-02	4.84 E-01	4.01 E-02	1.69 E-05	1.36 E-02	0.26749	0.301245	9.71 E-01	-3.83E-03
12	1.45E-02	4.87 E-01	4.65 E-02	1.89 E-05	1.73 E-02	0.335	0.1675	4.87 E-01	4.87E-01

Table.3. Parameters for Estimating the Color Features

Sl. No	Mean	Standard Deviation	Skewness	Kurtosis
1	0.899	0.913	1.243	0.33
2	0.927	0.9535	1.3115	0.358
3	0.98	0.8855	1.2965	0.411
4	0.791	0.8345	1.0565	0.222
5	0.878	0.8835	1.1925	0.309
6	0.889	0.8985	1.2185	0.32
7	0.908	0.886	1.225	0.339
8	0.864	0.907	1.202	0.295
9	0.95	0.9745	1.3555	0.381
10	0.999	0.967	1.397	0.43
11	0.935	0.9565	1.4345	0.478
12	0.978	0.489	0.898	0.409
Average	0.917	0.879	1.236	0.357

The Table.2 shows the various centric values obtained in determination of the texture features which is intentionally used for the determination of the Herbs in Hills taken images. The average value of the Energy is obtained as 1.61E-02, and Entropy is found as 4.48E-01. The variation in sum and difference is obtained as 8.94E-01 and 6.44E-04 respectively. The correlation and inversion value is obtained to be 2.09E-05 and 1.47E-02 respectively. The graph showing the texture features estimation is shown in Table.2.

Most important feature for the identification of the Herbs is the determination of the color features. Mostly the skewness rate and kurtosis rate are determined for the selection of the color features. The various parameters responsible for the determination of the color features are shown in Table.3.

The average value of the mean, standard deviation, skewness rate and kurtosis are determined as 0.9165, 0.879041667, 1.235875 and 0.356833333 respectively. The graph illustrating the color feature estimation is shown in Table.3.

The background information is totally taken out from the obtained images. At the beginning stage ANN is trained with 55 different features indicating the color, shape and the textures. While testing the leaf images of the Herbs with different classes the accuracy of the FHANN is obtained to be 96.27%. The computational costs are identified to be 58.25s. The neural network is trained separately along with the available input feature values. Hence the analysis is extended for determining the features of the leaves. Then the accuracy, precision, and recall are obtained as shown in Table.4.

Table.4. Different input feature Combination in consideration with Accuracy, Precision and Recall

Attributes	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Shape	75	96	78
Colour	86	92	84
Textures	84	90	76

Here the accuracy is obtained for different attributes like shape, colour and textures. The accuracy values for shape are 75% and precision value is 96%. The recall value is identified to be 78%. The colour attributes are identified to be 86% accuracy, 92 % precision and 84% recall value. For textures the accuracy value is 84%, precision value is 90% and recall value is 76%.

The estimation of the Herbs from the mountain areas are initiated successfully with the help of feature extraction techniques in association with the ANN and KNN. The method used here is a hybrid one and it shows better performance when compared with all other methods.

6. CONCLUSION

The fuzzy empowered Hybrid artificial neural networks (FHANN)-based plant identification and tracking system are proposed. The video signals captured by the drone camera are used as input. The video signals that are fed into the system are transformed into visuals. For the classification of the specific herbs from the set of plants, fuzzy logic and HANN are utilised. Parsley, Dill, Oregano, Chervil, Stevia, Basil, Catnip, Fennel, and Lemon Grass are among the herbs examined. In conjunction with fuzzy logic, this strategy uses artificial neural networks (ANN) in combination with the K-Nearest neighbour (KNN) as a hybrid model for herb prediction and categorization. For feature extraction from the acquired images, a hybrid model of Linear Discriminant Analysis (LDA) and Convolutional Autoencoder is applied. This method considers a variety of forms, colours, and textures to represent the many plants. The results of the experiments reveal that the proposed model performs better in terms of identifying and classifying therapeutic herbs.

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