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ORIGINAL

An Optimized Intelligent Deep Network for Herbal Leaf Classification

Una red profunda inteligente optimizada para la clasificación de hojas de hierbas

Hema Deepika A[1], Elango NM[1]

[1]Research Scholar, School of Computer Science Engineering and Information Systems Vellore Institute of Technology. Vellore, Tamil Nadu, India.
[2]Associate Professor, School of Computer Science and Engineering, Vellore Institute of Technology. Chennai, Tamil Nadu, India.

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ABSTRACT

In recent times, a variety of industries have made extensive use of image processing techniques for tasks including segmentation and classification. However, the traditional image processing and ensemble learning approaches face challenges in feature selection and classification. To overcome the demerits of the conventional image processing and boosting algorithm, a novel hybrid Chimp-based Boltzmann Prediction Network (CbBPN) was developed in this article. The presented work was designed and verified in MATLAB software with the herbal leaf dataset. In the model development, the pre-processing and feature extraction module is responsible for extracting valuable features that are pertinent to the classification process. Furthermore, the chimp fitness function increases the classification rate by removing unwanted elements during the classification stage. Additionally, the developed model uses the matching operation to specify the types of the leaf. Furthermore, a case study was created to explain the ways the suggested approach operates. Moreover, a comparison of the projected findings with the existing categorization approaches validates the effectiveness of the constructed model. The comparative analysis shows that the new methods outperformed previously available ones in terms of output.

Keywords: Chimp Optimization Algorithm; Boltzmann Prediction Network; Herbal Leaf Classification; Leaf Type Specification.

RESUMEN

En los últimos tiempos, una variedad de industrias han hecho un uso extensivo de técnicas de procesamiento de imágenes para tareas que incluyen segmentación y clasificación. Sin embargo, los enfoques tradicionales de procesamiento de imágenes y aprendizaje por conjuntos enfrentan desafíos en la selección y clasificación de características. Para superar los inconvenientes del algoritmo de mejora y procesamiento de imágenes convencional, en este artículo se desarrolló una novedosa red híbrida de predicción de Boltzmann (CbBPN) basada en chimpancés. El trabajo presentado fue diseñado y verificado en el software MATLAB con el conjunto de datos de hojas de hierbas. En el desarrollo del modelo, el módulo de preprocesamiento y extracción de características es responsable de extraer características valiosas que son pertinentes para el proceso de clasificación. Además, la función de aptitud del chimpancé aumenta la tasa de clasificación al eliminar elementos no deseados durante la etapa de clasificación. Además, el modelo desarrollado utiliza la operación de coincidencia para especificar los tipos de hoja. Además, se creó un estudio de caso para explicar las formas en que opera el enfoque sugerido. Además, una comparación de los hallazgos proyectados con los enfoques de categorización existentes valida la efectividad del modelo construido. El análisis comparativo muestra que los nuevos métodos superaron a los disponibles anteriormente en términos de producción.

Palabras clave: Algoritmo de Optimización de Chimpancés; Red de Predicción de Boltzmann; Clasificación de Hojas de Hierbas; Especificación del Tipo de Hoja.

INTRODUCTION

Image processing is nothing but for presenting various processes from the image, getting an improved image, and extracting some useful evidence from the particular images.[1] Signal processing is also image processing; in this case, the image served as the input and some of its associated features served as the output. Image processing includes improving images, encoding, compression, and re-establishment.[2] Moreover, these image processing methodologies were utilized to find numerous characteristics and patterns of the input images[3] Identifying the pattern of the images was utilized for analyzing the handwriting, Computer-aided medical analysis, and recognition of the images.[4]

However, some of the uses of image processing[5] mechanism are the improved version of images for human interpretation[6] the data were processed and executed among the images for machine interpretation[7] algorithms were used in image processing to identify and detect the different essential parameters in the particular parts of the input images[8] using the image processing mechanism, the classification of herbal leaves is illustrated in figure 1. Image processing consists of different phases, namely, importing images and analyzing the images. Then the last stage was manipulation and the output[9] furthermore, two image processing techniques were applied: digital image processing and analogue image processing.[10] One of the key areas of study for deep learning,[11] machine learning,[12] and image processing was the analysis of herbal plants. Here, to classify as well as identify the plant, the characteristics of the leaf were used. Leaf characteristics vary, like shape and size variations.[13] Furthermore, from a single plant, leaves of various categorization shapes and sizes were selected.[14] The automated model of the system was utilised to compute the different leaf attributes, such as the leaf's area, width, and length.[15]

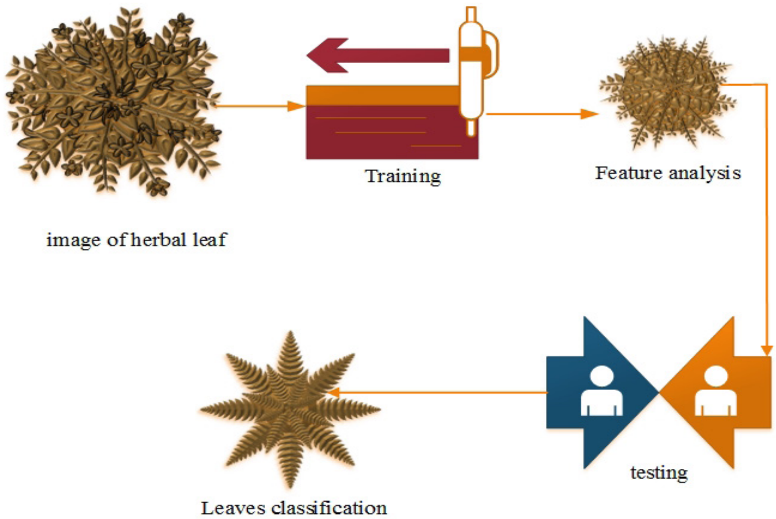

Figure 1. Herbal Leaves classification

However, the mobile images were resized for further classification and analysis. [16] For extracting the leaf features, pre-processing mechanisms were applied to change the images from color to greyscale.[17] Classifying the herbal leaves along with image processing[18] and support vector machine techniques[19] does not provide accurate results for precision and recall, so the proposed model was developed to get better precision than the recall rate.

The study that is being presented is organised as follows: the second section describes the works that are related to the classification of herbal leaves; the third section discusses the issues and difficulties with the current leaf classification techniques; the fourth section details the presented model and includes an algorithm and flowchart; the fifth section illustrates the study's overall discussion and performance validation; and the sixth section mentions the article's conclusion.

Related Works

The following is a sample of recent research on the categorization of herbal leaves:

Muneer et al.[20] have suggested the Effective and Mechanised Herbs Organization Method Based on Texture and shape Features by Deep Learning mechanism. This research used effective and automated classification schemes for recognizing Malaysian herbal leaves for cooking or medical areas. The proposed section examined different classifiers for developing an effective classifier. Then the classifiers were combined with the mobile applications to make a simple classification in real-time. In this research, Deep Learning Neural networks (DLNN) and Support Vector Machines (SVM) were used to test more leaves. But, DNN needs more amount of input data to provide better results.

Therefore, Azadnia et al.[21] have provided the Recognition of leaves based on different medicinal plant classifications using a healthy image processing approach and artificial neural networks classifier in order to acquire better results with a limited amount of input data. This was followed by the suggestion of a trustworthy automatic image processing technique for the timely identification of medicinal plants under the observed conditions. The algorithm's development process began with the extraction of features from the supplied input photos, such as colour and shape. Artificial neural Networks were given for classifying the different groups of medicinal plants. Then the classifier's effectiveness was chosen based on the accuracy, correlation, and error. However, artificial neural networks depend on the hardware.

Chouhan et al.[22] proposed a Data Repository of Leaf Images: Practice towards Plant Conservation with Plant Pathology. The relationship between the environment and the plant was complex and countless. Plants were considered the important element in the production of carbon and then climatic changes. In this research, 4503 images were collected. Among them, 2 278 images were considered healthy, and 2 225 images were unhealthy leaves. Consequently, the Data Repository study provides more uses for the researchers, like identification of plants, monitoring the growth of plants, classification of plans, and examining the leaf infection. However, Data Repository contains more amounts of data which slows down the systems.

Mettripun[23] was used to show Thai Herb Leaves Classification Based on Properties of Image Regions. Classifying Thai herb leaves is suggested by this study based on the characteristics of the image regions. Additionally, the results of the pre-processing, feature extraction, and grouping are provided by the suggested model. Pre-processing was used to alter the leaf's color. Then the leaf's aspect ratio, eccentricity, extent, perimeter, and circularity were used to extract the features. After completing the feature extraction process then, the ANN helped to group. Hence, through this average research amount of accuracy was attained.

The identification of toga plants (specifically, Tanaman Obat Keluarg) based on leaf images using edge detection features and invariant moment has been proposed by Asmara et al.[24] The majority of methods for determining the kind and productivity of the TOGA plant are more complicated. In this research, the toga plant was identified through the image of the leaf. Using Invariant Moment and Canny edge, the toga leaf's image was extracted, and the leaf type was determined using the K-Nearest Neighbor model. However, the KNN model did not provide better results for larger data sets.

The present study's key contribution is expounded upon as follows:

- Initially, a system that contains many herbal leaf image data sets was trained using the collected leaf data.
- Consequently, a novel CbBPN functioned to predict each leaf's features and categorize the leaf type.
- Furthermore, the pre-processing function is carried out in the CbBPN second phase in order to obtain the best filtering result.
- After the noise filtering process, the input exits type classification and enters the classification layer for feature extraction.
- The accuracy, precision, recall, F-measure, and error rate of the herbal leaf type classification are examined in relation to the improvement score.

System Model with Problem Statement

In data science, several neural networks are employed for classification and prediction tasks. However, the conventional boosting approach in herbal leaf prediction consumes more time. Furthermore, it is challenging for the conventional neural approach with boosting algorithm to predict and classify the leaves if the dataset is large and complex. DL mechanisms were put in place in consideration of all these problems; however, they have taken more time and resources when dealing with large amounts of complex data.

In existing DL approaches, the leaf dataset is segmented, and the edges of the leaf image are detected. Furthermore, the features are selected and processed. Then, the leaves are classified based on the selected features. Here, only a small amount of features are selected. This results in a very low specification rate. Consequently, the current effort aims to design new, optimised deep networks for herbal leaf classification and prediction. The system model and its problem statement are displayed in figure 2.

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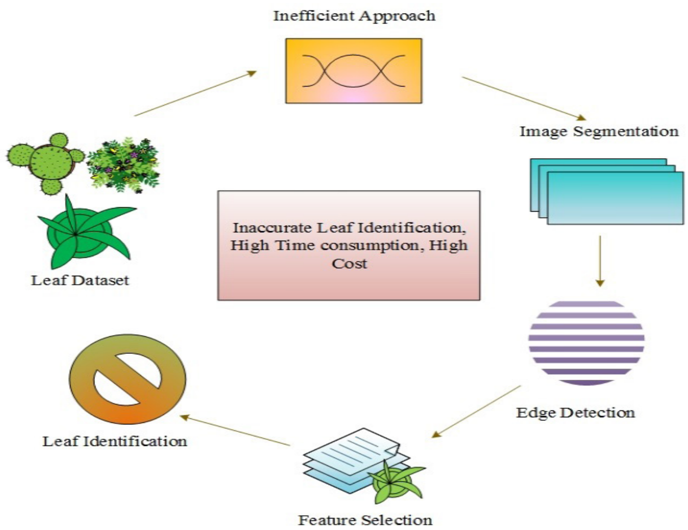

Figure 2. System Model and its Problem Statement

Proposed CbBPN for Herbal Leaf Classification

A novel Chimp-based Boltzmann Prediction Network (CbBPN) was developed to recognize and classify the herbal leaves. This presented approach hybrids the Chimp optimization algorithm[25] and the Boltzmann Prediction Network[26] Initially the MATLAB system imports the herbal leaf dataset that was gathered from the standard website, Kaggle. After that, the error features are eliminated by pre-processing and training the dataset. Additionally, the feature analysis module extracts the significant features.

Here, during execution, the features of each herbal leaf were saved in the chimp memory function, and the herbal leaves were categorized using the features that had been saved. Finally, the saved features are used to specify the leaf types. Here, the Boltzmann network's classification layer has adopted the chimp algorithm procedure. The proposed approach is depicted in figure 3. The classification rate is increased by incorporating chimpanzee fitness into the proposed model. Lastly, using additional modern models, the performance score has been quantified and verified.

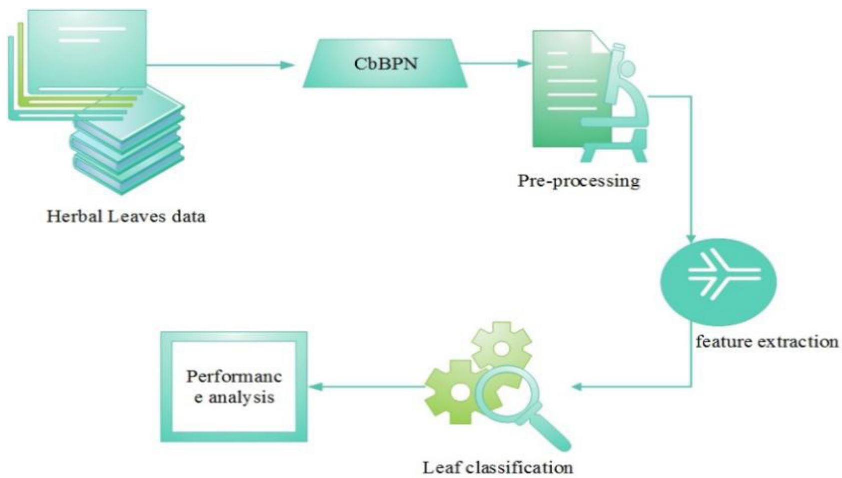

Figure 3. CbBPN Framework

Pre-processing Module

After being collected at the standard site, the leaf dataset was initially loaded into the system. Next, the dataset is initialised and trained by the system. The dataset is initialised and trained on the model's input layer. Equation (1) depicts the initialization of the dataset.

$$\tilde{f}\left(L_d(l_e)\right)=T\left(l_{e1},l_{e2},l_{e3},l_{e4},\ldots,l_h\right) \quad (1)$$

Where *f* represents the function for initializing a dataset. L_d displays the leaf dataset. l_e indicates the leaf data, *h* is used to describe the total number of data in the dataset and *T* shows the characteristics found in the dataset. Next, the system uses the developed algorithm to train the dataset. Preprocessing is done on the trained dataset to eliminate any noise features. The dataset's null, error, and noise features are removed during the pre-processing stage. Therefore, the prediction and classification rate are improved by this filtering mechanism. The pre-processing function is expressed in equation (2).

$$\rho^{*}(L_d) = \left| \lambda \,.\, l_{eh} - l^{\circ}_{eh} \right| \quad (2)$$

Here, ρ denotes the pre-processing function, λ indicates the pre-processing variable, and l°_{eh} indicates of the error characteristics found in the dataset. In this case, the pre-processing of the dataset is done using the chimp optimization algorithm concept.

Feature Analysis

The pre-processed dataset is used in this module to extract the characteristics that are useful for prediction and classification. The pre-processed dataset contains meaningful features as well as meaningless features. Here, the dataset's ineffective features are disregarded. The feature track is expressed in equation (3).

$$\Delta(L_d) = \sigma(ml_e, m^{*}l_e) \quad (3)$$

First, the current features within the dataset are monitored. Here, Δ indicates the function of feature tracking, σ shows the variable for feature tracking, ml_e represents the meaningful leaf features and $m^{*}l_e$ refers to the featureless aspects. Subsequently, the dataset's tracked useless features are removed. In equation (4), the feature extraction is expressed.

$$\mu(L_d) = \frac{1}{\sigma}\left[\exp\left(-E(ml_e, m^{*}l_e)\right)\right] \quad (4)$$

Here, μ represents the function for feature extraction. As a result, the dataset's significant features are extracted. In addition, the system is trained to forecast the herbal leaves using the extracted attributes.

Leaf Classification

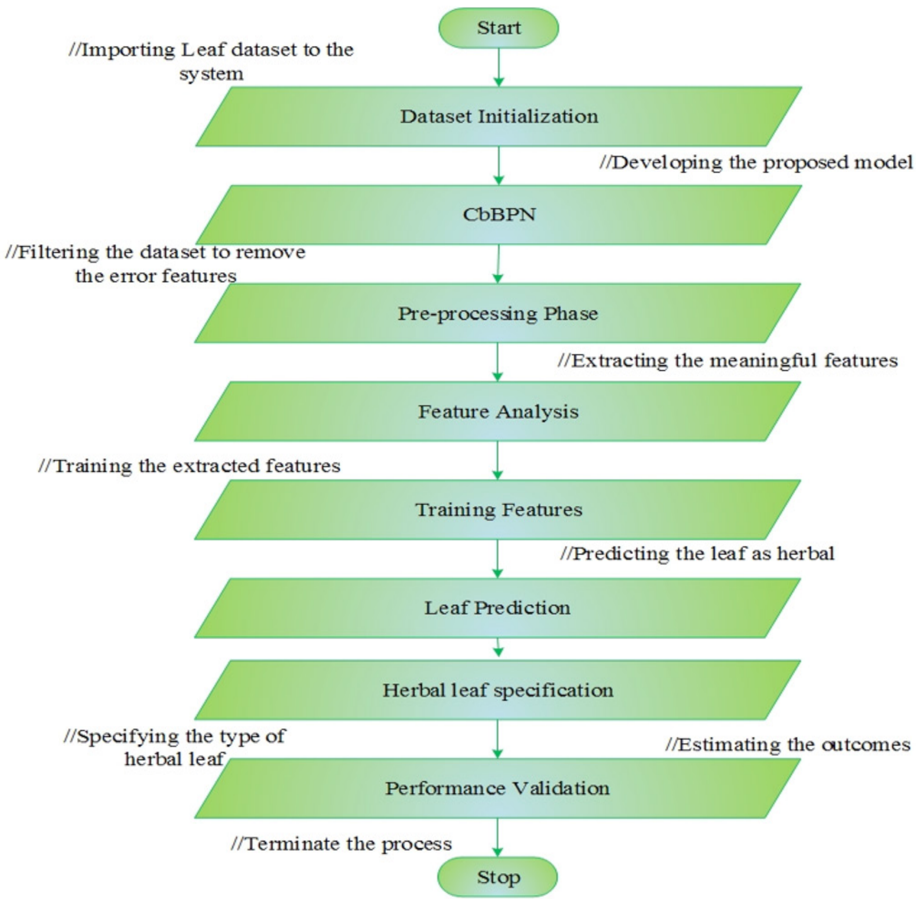

Figure 4. shows the flowchart of the developed model. Additionally, algorithm 1 provided a pseudocode explanation of the model that was presented. Lastly, to verify the developed

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The retrieved and trained features are used by the created model's classification layer to identify the herbal leaves from the image dataset. Here, the leaves are classified based on the trained features. The leaf types are specified by matching the trained leaf feature with the test leaf feature. The leaf type is specified if the trained leaf features match the test leaf features. It is expressed in equation (5).

$$Lt_S = \sum_{i=1}^{h} matches(Hf, l_e) \quad (5)$$

Where Lt_s represents the leaf type specification function, Hf indicates the trained leaf features, and *matches* denotes the function. Thus, the herbal leaf types are specified by comparing the herbal features of the leave with the presented leaf features.

RESULT AND DISCUSSION

This article developed a hybrid classification model to identify and categorize the herbal leaves. The herbal leaf dataset was used to validate the model that was presented. First, pre-processing and training are applied to the dataset in order to remove any noisy features. Furthermore, the characteristics are extracted via the feature analysis module. The herbal leaf is then classified by training the extracted features with the created model. Additionally, the matching function is used to specify the type of herbal leaf.

Case Study

To show how the proposed model is applied, a case study is presented. First, MATLAB was used to import the standard herbal leaf dataset that was collected from the Kaggle website. A unique classification model with appropriate prediction parameters was created by the system. The system then initialises and trains the input dataset in the input layer. To further remove noisy data, the learned dataset is pre-processed. There are features in the pre-processed data that are both significant and insignificant. The feature extraction module eliminates the features that have no meaning from the dataset.

Additionally, the developed model is used to train the meaningful features that have been extracted in order to classify the herbal leaf. In this case, the trained features were used to perform the classification. It was decided to include a matching function to indicate the kind of herbal leaves. Assume that the features in the dataset correspond to the herbal features, and that the appropriate kind of herbal leaf was identified. The developed model's workflow is depicted in figure 5. Finally, the robustness of the new model was confirmed by comparing the results with the earlier approaches.

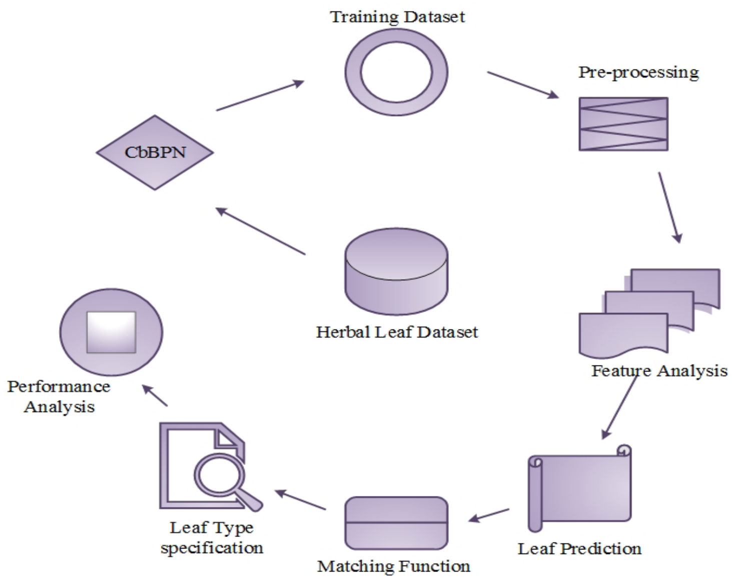

Figure 5. Workflow of CbBPN

The sample dataset images are represented in figure 6. The input dataset contains 10 different classes, namely, adamant creeper, Aloe vera, Bermuda grass, betel, Datura, Indravalli, Nathiyavatti, neem, puncture vine, and Tulsi. In each class, 100 images of the herbal leaves are present. Figure 6(a) presents the sample image of adamant creeper, figure 6(b) represents the sample image of Aloe vera.

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(a) (b)

Figure 6. Sample Dataset Images: (a) Adamant Creeper, (b) Aloevera

The sample output image is shown in figure 7. Here, the herbal leaf types are specified by matching the features of all trained leaves with the test leaf features. Figure 7(a) represents the sample output for puncture vine specification, and figure 7(b) displays the output sample for Tulsi specification.

(a) (b)

Figure 7. Sample Output: (a) Puncture Vine, (b) Tulsi

Comparative Analysis

An evaluation that was comparative served as validation for the designed model's efficiency. Here, the estimated results are compared with the methods that are currently in use for metrics like recall, f1-score, accuracy, and precision. The current methods employed for comparative analysis are Herb Classification based on Deep Learning Neural Network (HCbDLNN)[20] Herb Classification based on Support Vector Machine (HCbSVM)[20] and Automated Herb Classification System based on Convolutional Neural Network (ASbCNN).[27]

Precision

The correct positive leaf prediction and classification attained by the system out of all positive prediction and classification is defined as precision. It can be determined by dividing the true positive score by the true and false positive values. It is formulated in equation (6).

$$P = \frac{tx}{tx + fx} \quad (6)$$

Here, P denotes the precision value, *tx* indicates the true positive, and *fx* stands for the false positive.

To show that the developed model achieved a greater accuracy value than the previous approaches, its precision is compared with existing approaches. Here, approaches such as ASbCNN, HCbDLNN, and HCbSVM are used for comparative analysis. The obtained model's amount of precision is 99,9 %. However, the current methods produced low precision values of 66,4 %, 93 %, and 75 %, respectively. The comparative analysis demonstrates that the generated model outperformed the others in terms of precision value. Figure 8 shows the comparison of precision with others.

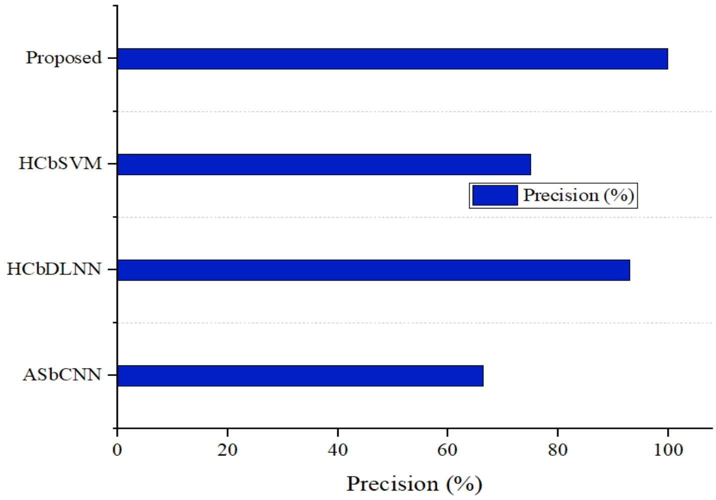

Figure 8. Comparison of Precision

Accuracy

The accuracy of the system is known as the herbal leaf classification rate. Out of all the predicted outcomes, it shows the precise prediction and classification. Its assessment is determined by adding together and separating the genuine up-sides and negatives by the valid and bogus up-sides and negatives. The system accuracy is formulated in equation (7).

$$Aq = \frac{tx + ty}{tx + ty + fx + fy} \qquad (7)$$

Here, *Aq* demonstrates the accuracy of the framework, *ty* indicates the false negative and *fy* represents the false negatives.

Figure 9 shows the comparison of accuracy. The developed model's rate of leaf classification is 99,8 %, whereas the existing approaches such as ASbCNN, HCbDLNN, and HCbSVM earned 71,3 %, 93 %, and 74,63 %, respectively. The developed model's chimp fitness function increases the classification rate. This shows that the developed model attained high classification than others. The made model's high characterization rate demonstrates that it can exactly recognize and determine natural leaves.

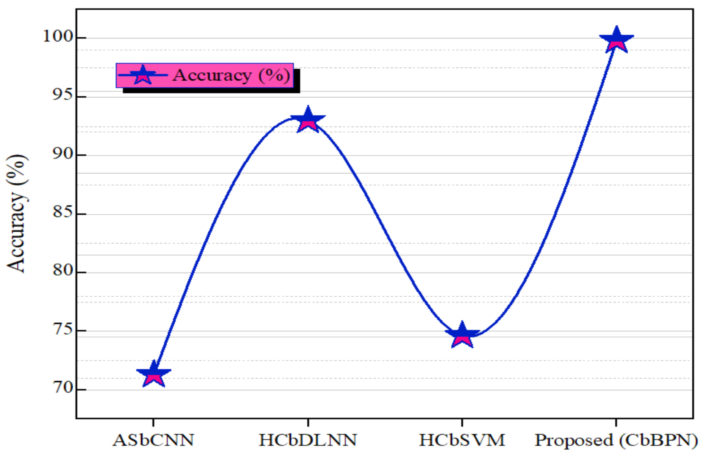

Figure 9. Comparison of Accuracy

Recall

The recall value shows how many herbal leaves were actually imported into the system as opposed to how many the system anticipated. It can be estimated by dividing the true positive by the sum of the true positive

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and false negative. The system's recall is represented by equation (8).

$$Rl = \frac{tx}{tx + fy} \quad (8)$$

Here, *Rl* refers to the recall:

The system's real prediction is verified through comparison with the current methodologies. Here, the current methods, like ASbCNN, HCbDLNN, and HCbSVM, obtained a recall percentage of 67,8 %, 85 %, and 71 %, respectively. Figure 10 shows the comparison of recall percentages. The created model achieved a recall percentage of 99,8 %, which is high compared to existing approaches. This indicates that the generated model has a high prediction rate.

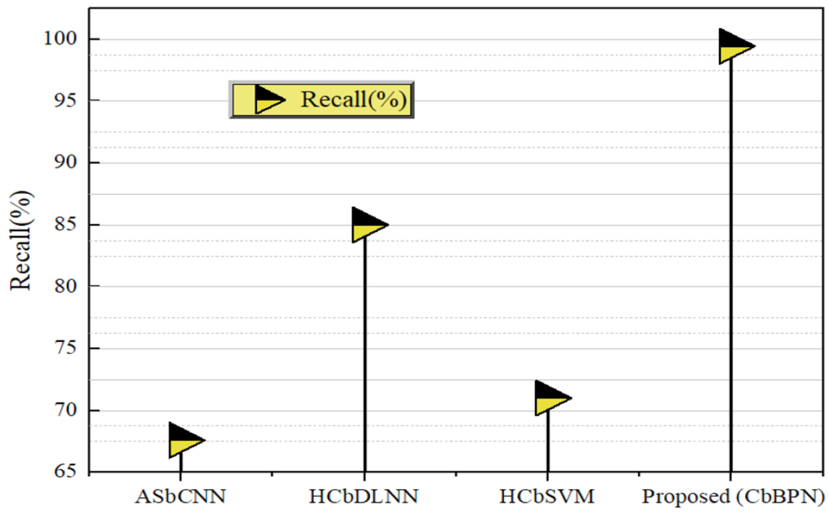

Figure 10. Comparison of Recall

F1-score

The F1-score is the mean capability between the review and accuracy of the framework. Still up in the air by partitioning the result of review and accuracy by their aggregate. The estimation of accuracy is addressed by equation (9).

$$F1 - score = 2 \times \left[\frac{P \times R}{P + R} \right] \quad (9)$$

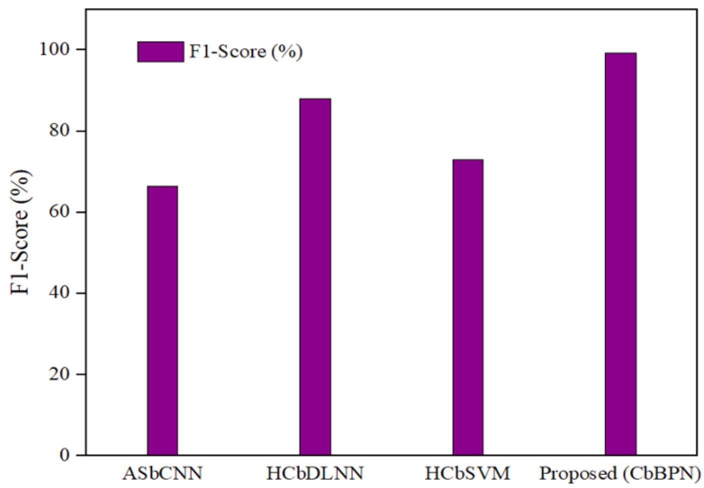

Figure 11. Comparison of F1-score

The comparison of the F1-score is shown in figure 11. The f1-score got by the created model is 99,32 %. However, the current methods such ASbCNN, HCbDLNN, and HCbSVM achieved lesser f1-score of 66,4 %, 88 %, and 73 %, respectively. This shows that the developed model attained a higher f1 score than other existing approaches.

Moreover, table 1 tabulates the overall comparative evaluation. The aftereffects of the exhibition and near examination show that the created model beat the ongoing techniques in accomplishing improved results. Additionally, the comparative analysis is used to estimate the performance enhancement score.

Table 1. Statistical Comparative Assessment

Techniques	Accuracy (%)	Precision (%)	F1-score (%)	Recall (%)
ASbCNN	71,3	66,4	66,4	67,6
HCbDLNN	93	93	88	85
HCbSVM	74,63	75	73	71
Proposed (CbBPN)	99,84	99,90	99,32	99,45

Discussion

Using MATLAB software, the suggested leaf classification method was put into practice and tested on a dataset of herbal leaves. The leaf dataset was first assembled and added to the framework. The dataset is then pre-handled and prepared to overlook the commotion highlights. Furthermore, the component extraction module extricates the elements that are useful for arranging and recognizing leaves. Furthermore, the developed model specifies the herbal leaf types using the matching function.

At long last, the model that was recently introduced was tried, and the outcomes are assessed regarding review, exactness, accuracy, and f1-score. A similar evaluation was likewise used to approve the fostered model's heartiness. As a result, the system correctly identifies and classes the leaf type. Figure 12 illustrates the designed model's performance.

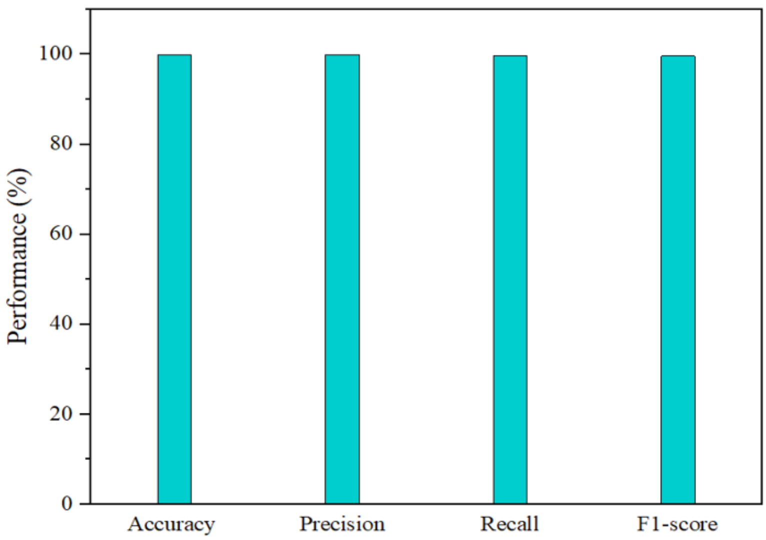

Figure 12. Performance of CbBPN

CONCLUSION

A novel CbBPN was designed in the presented work to identify and specify the herbal leaves and their types. The introduced work was approved with a home grown leaf dataset. The chimp wellness capability is coordinated into the secret period of the created model to pre-process the dataset. Additionally, the classification phase extracts the useful features to identify the type of leaf. In addition, the herbal leaf types are specified using the matching function. At long last, the outcomes are assessed in execution examination. The presentation evaluation shows that the planned model acquired higher exactness of 99,8 %, a greater recall of 99,8 %, and an improved precision value of 99,45 %. Additionally, a comparative assessment is used to confirm and validate the developed model's efficacy. Here, the boundary upgrade score is additionally assessed and the assessed results are contrasted and the current strategies, including ASbCNN, HCbDLNN, and HCbSVM. The relative factual examination shows that in the planned model, the exactness rate is improved by 6,48 %, recall is improved by 14,58 %, and the f1-score is improved by 6,54 %. Subsequently, the created model recognizes and groups the natural leaves precisely.

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Data curation: Hema Deepika A.
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Research: Elango NM.
Methodology: Hema Deepika A.

Drafting - original draft: Elango NM.
Writing - proofreading and editing: Elango NM.