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Research Article

Dry Ayurvedic Herbs

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Identification of Dry Ayurvedic Herbs (Fruits and Seeds) through Computer Vision Technology

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The study investigates the use of Computer Vision Technology (CVT) combined with Convolutional Neural Networks (CNNs) to address challenges in the identification of dry Ayurvedic herbs (fruits and seeds). A dataset of 50,000 high-resolution images, encompassing 50 herb species, was utilized to train a CNN model. The architecture comprised convolutional layers with filters and Dropout layers, ensuring efficient feature extraction and overfitting mitigation. The model achieved a peak training accuracy of 91.86% and a validation accuracy ranging from 81% to 83%, with an inference time of 36 milliseconds per step, indicating its potential. Performance evaluations, including accuracy metrics and confusion matrices, highlighted high prediction rates for distinct species. However, misclassifications among visually similar herbs underscored the need for dataset expansion and further optimization. Recommendations include incorporating robust database, additional species, diverse angles, and lighting conditions, as well as addressing class imbalances through data augmentation or resampling. Advanced regularization techniques, are proposed to enhance generalization. This research work Bridges the Traditional identification methods and Modern methods with Technology and establishes a robust framework for leveraging AI and computer vision in Ayurvedic herb identification, contributing significantly to the modernization and quality assurance of traditional herbal medicine. The findings emphasize scalability and future integration of cloud-based systems for large-scale applications.

Keywords: Ayurvedic herbs, Artificial intelligence, Computer Vision Technology, Convolutional Neural Network, Image Classification

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Introduction

The identification and quality control of *Ayurvedic* herbs are critical to ensuring the safety, efficacy, and consistency of traditional medicinal formulations. *Ayurveda*, an ancient system of medicine, relies heavily on the use of herbs, including fruits and seeds, to treat a variety of ailments. However, the accurate identification of dry herbs, especially in their dry forms, poses a significant challenge due to the morphological similarities among species, the presence of adulterants, and the lack of standardized methods for quality control. And hence adulteration is prevalent; for example, seeds from *Carica papaya* are sometimes misbranded as *Piper longum*, and *Cinnamomum cassia* is often sold as *Cinnamomum zeylanicum*, despite significant differences between them.**[1]** The Ayurvedic Pharmacopoeia of India (API)**[2]** prioritizes macroscopic examination based on visual characteristics for identifying herbal drugs. Acc. to WHO macroscopic examination of herbal materials provide a straightforward and rapid method to determine their identity.**[3-5]** However, traditional methods face challenges in a global market, necessitating advanced technologies such as Computer Vision Technology (CVT) and molecular analysis. Applications like Ayurleaf**[6]** and Leafsnap**[7]** are example of this. Similarly, Praman AI,**[8]** an app focused on the cardamom trade, uses AI for post-harvest quality assessment, streamlining agricultural processes and ensuring product quality. Computer vision and Artificial intelligence-based modelling are explored by many researchers in recent time for industrial application. Despite the success of these technologies, the application of computer vision for dry Ayurvedic herb.

The emphasis of presented study was on the training a model on the macroscopic features of 50 (fruits and seeds) commonly traded dry herbs through Computer Vision technology using the Multiclass classification and Convolutional neural network approach. The basic concept of NN and Artificial Intelligence with the proposed architecture with detailed parameters are given in the manuscript. The results have been explored and discussed along with the conclusion of paper with further future scope of the presented study. Here is the list of Dry *Ayurvedic* herbs which were used in the study.

Table 1: List of Dry Herbs used in this project

SN	Name	Botanical Name	Family	Part Used
1.	Bhallatak	Semicarpus anacardium	Anacardiaceae	Fruit
2.	Pippali	Pipier longum	Piperaceae	Fruit
3.	Amla	Embillica officinalis	Euphorbiaceae	Fruit
4.	Bibhitaki	Terminali bellarica	Euophorbiaceae	Fruit
5.	Jatiphal	Myristica fragrans	Myristicaceae	Fruit
6.	Badi ela	Amomum subulatum	Zingiberaceae	Fruit
7.	Haritaki	Terminalia Chebula	Euphorbiaceae	Fruit
8.	Madanphal	Randia spinosum	Rubiaceae	Fruit
9.	Shleshmatak	Cordia dichotoma	Boragenaceae	Fruit
10.	Gokshur	Tribulus terrestris	Zygophyllaceae	Fruit
11.	Dadim	Punica granatum	Punicaceae	Fruit
12.	Kankol	Piper cubeba	Piperaceae	Fruit
13.	Unnav	Ziggiphus sativa	Rhamnaceae	Fruit
14.	Bilva	Aegle marmelos	Rutaceae	Fruit (Majja)
15.	Aragvadh	Cassia fistula	Fabaceae	Fruit (Majja)
16.	Gunja	Abrus precatorius	Fabaceae	Seed
17.	Poog	Areca catechu	Arecaceae	Seed
18.	Badi kateri	Solanum indicum	Solanaceae	Fruit
19.	Erand	Ricinus communis	Euophorbiaceae	Seed
20.	Kaarvelaak	Momordica caharantia	Cucurbitaceae	Fruit
21.	Palash	Butea monosperma	Fabaceae	Fruit
22.	Vishala	Citrallus colocynthis	Cucurbitaceae	Fruit
23.	Draksha	Vitis vinifera	Vitaceae	Fruit
24.	Vidanga	Embelia tsjeriam-cottam	Myrsinaceae	Fruit
25.	Ela	Elettaria cardamomum	Zingiberaceae	Fruit
26.	Laung	Syzygium aromaticum	Myrtaceae	Fruit
28.	Kuchla	Strychnous nux-vomica	Loganiaceae	Seed
29.	Nirgundi	Vitex negundo	Verbenaceae	Seed
30.	Til	Sesamum indicum	Pedaliaceae	Seed
32.	Konch	Mucuna pruriens	Fabaceae	Seed
33.	Shatpushpa	Anethum graveolens	Umbelliferae	Seed
34.	Jambu	Syzigium cumini	Myrtaceae	Seed
35.	Kamal	Nelumbo nucifera	Nymphaceae	Seed
36.	Latakaranja	Cessalpinia crista	Cesalpainodae	Seed
37.	Jaipal	Croton tiglium	Euphorbiaceae	Seed
38.	Upkunjika (kalonji)	Nigella sativa	Ranunculaceae	Seed
39.	Indrayav	Holarrhena dysentrica	Apocynaceae	Seed
40.	Methi	Trigonella foenum-graecum	Fabaceae	Seed
41.	Karanja	Pongamia pinnata	Fabaceae	Seed
42.	Shvet jeera	Cuminum cyminum	Apiaceae	Seed
43.	Kali mirch	Piper nigrum	Piperaceae	Seed
44.	Dhaanyak	Coriandrum sativum	Apiaceae	Seed
45.	Neem	Azadirachta indica	Meliaceae	Seed
46.	Yavani	Tachyspermum amii	Apiaceae	Seed
47.	Javitri	Myristica fragrans	Myristicaeae	Aril
48.	Maalkaangni	Celastrus paniculatus	Celastraceae	Seed
49.	Sauf	Foeniculum vulgare	Umbelliferae	Seed
50.	Jambu	Syzigium cumini	Myrtaceae	Seed

Neural Network

An Artificial Neural Network (ANN) is designed to replicate the structure and functionality of neurons in the human brain, enabling it to understand non-linear physical processes.[9,10] ANNs are built by creating artificial neurons and interconnecting them in a way that emulates the behaviour of interconnected brain cells. When these networks contain a large number of neurons (nodes) arranged in layers, they are referred to as Deep Neural Networks (DNNs). NNs have revolutionized artificial intelligence by providing the capability to understand and solve a wide range of complex real-world problems. These networks are characterized by an architecture that includes a single input layer, multiple hidden layers for learning non-linear patterns from input data, and a final output layer. Each layer contains numerous neurons, where each neuron processes multiple inputs according to an activation function and transmits the computed output to the subsequent layer, as illustrated in Fig.1 The inputs ("x1, x2, … xi … xn") are referred to as input nodes, while the outputs ("y1, y2, … yi … ym") are called output nodes of the network.[11]

For a logistic regression problem, there is typically one output node; for binary classification, number of output nodes is two; and for more complex problems, the number increases. A typical DNN, depicted in Fig.2, comprises multiple hidden layers that enable network to learn complex features and non-linear patterns from input data. Each layer processes outputs of the previous layer using its neurons (nodes), and final layer produces the overall output of the network. The layers in a DNN are connected by a set of weights ("w1, w2, … wi … wl"), which are adjusted during training process to optimize performance.[12,13]

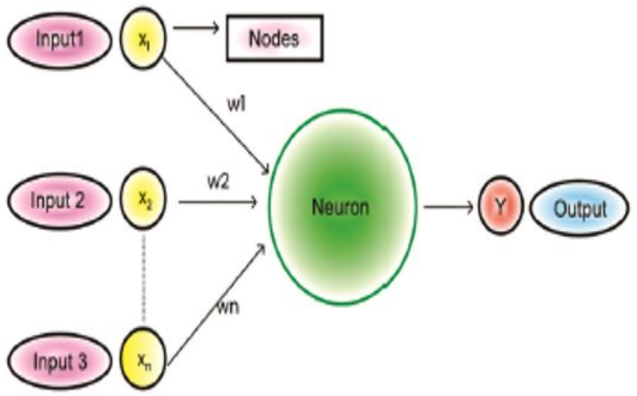

Figure 1: Basic structure of Neural Network

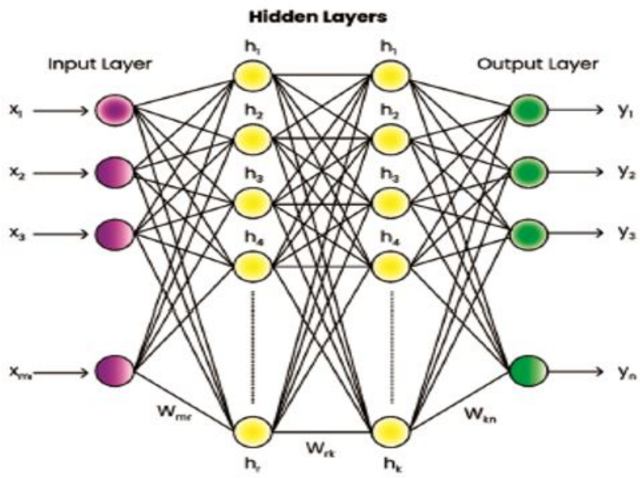

Figure 2: Deep Neural Network architecture

These weights play a crucial role in the computations and decision-making processes of a neural network during deployment. A well-trained network, developed using an appropriate dataset, demonstrates superior performance in unfamiliar real-world scenarios compared to an under-trained or over-trained network.

The greater the number of layers in a Deep Neural Network (DNN), the more complex features it can extract and learn from the input data. However, training a DNN with many layers presents significant challenges, as the training parameters, such as weights, learning rate, and gradients, can vary widely in scale. To address these challenges, an optimal configuration of nodes and hidden layers is carefully designed based on the characteristics of the dataset.

Materials

The study utilized a combination of literary sources, dataset creation, advanced imaging equipment, robust computational systems, and specialized software to achieve its objectives. Ayurvedic texts, journals, and modern resources were thoroughly reviewed to establish a connection between traditional herbal knowledge and image recognition technology.

A comprehensive dataset comprising 5,000 images (150-200 per herb) of 50 dry herbs, including 25 fruits and 25 seeds, was collected from Central Ayurved Research Institute-Jhansi and Departmental Museum of the IASR. High-resolution smartphones, such as the iPhone 14 and Motorola Moto Edge-5, were employed to capture detailed images of the herbs.

For image analysis, a powerful computer system featuring Intel Xeon processors and NVIDIA Tesla V100 GPUs was utilized. Additionally, various software tools, including Photoshop, TensorFlow, Keras, and Python libraries like OpenCV were employed to process and analyze the images effectively.

Methodology

1. Data Collection: Images were collected to cover diverse views for improved model

2. Pre-processing and Augmentation: Images were resized, normalized, and augmented for better model generalization.

3. CNN Model Development: A convolutional neural network (CNN) was trained for herb

4. API and UI Development: An API and user-friendly interface enabled image uploads and classification results.

5. System Integration and Testing: The system was integrated, tested, and deployed, followed by real-world evaluations.

Proposed Work

Ayurvedic herb identification through computer vision has been addressed using a Convolutional Neural Network (CNN). Traditional identification methods based on macroscopic examination are complex and time taking so need experts, making AI-driven approaches viable alternatives. The dataset comprising high-resolution images of dry Ayurvedic herbs were pre-processed and used to train the CNN model. Input parameters such as image size, batch size, and data augmentation techniques (random rotations, flips, and zooms) were optimized to enhance model generalization.

The model architecture includes a single input layer, three convolutional layers with filter sizes of 32, 64, and 128, followed by MaxPooling2D and Dropout layers. The fully connected dense layers culminate in an output layer with a softmax activation function for multi-class classification. The total trainable parameters in the model were computed as 8,784,273, shown in Fig 3. The ReLU activation function is applied to each neuron, introducing the required non-linearity, while the output layer uses softmax for probabilistic classification. The dataset, consisting of 5,000 images, was divided into training (70%), validation (20%), and testing (10%) subsets. Training was conducted over 20 epochs with a batch size of 51 using the Adam optimizer and categorical cross-entropy loss function.

The performance metrics such as accuracy, confidence and confusion matrix score were evaluated, with accuracy stabilizing at 90% by the 10th epoch as shown in Fig 4 & Fig. 5. The confusion matrix (Fig.6) highlighted high prediction accuracy, while some misclassifications indicated the need for further refinement. The optimized architecture with three hidden layers (16, 8, and 4 nodes) demonstrated a balance between model complexity and performance. This optimized CNN model, provides a robust framework for *Ayurvedic* herb identification and is suitable for large-scale practical applications.

Performance metrics such as confidence scores evaluated effectiveness, with a confusion matrix, as shown in Fig. 6 and Fig. 7 highlighting high prediction accuracy for classes. However, off-diagonal matrix values and fluctuating validation accuracy suggest overfitting and necessitate hyperparameter tuning (e.g., L2 regularization).

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_16 (Conv2D)          (None, 256, 256, 32)      896

 max_pooling2d_16 (MaxPoolin  (None, 128, 128, 32)     0
 g2D)

 conv2d_17 (Conv2D)          (None, 128, 128, 64)      18496

 max_pooling2d_17 (MaxPoolin  (None, 64, 64, 64)       0
 g2D)

 conv2d_18 (Conv2D)          (None, 64, 64, 128)       73856

 max_pooling2d_18 (MaxPoolin  (None, 32, 32, 128)      0
 g2D)

 dropout_12 (Dropout)        (None, 32, 32, 128)       0

 conv2d_19 (Conv2D)          (None, 32, 32, 256)       295168

 max_pooling2d_19 (MaxPoolin  (None, 16, 16, 256)      0
 g2D)
...
Total params: 8,784,243
Trainable params: 8,783,987
Non-trainable params: 256
```

Figure 3: Developed Model and Layers used

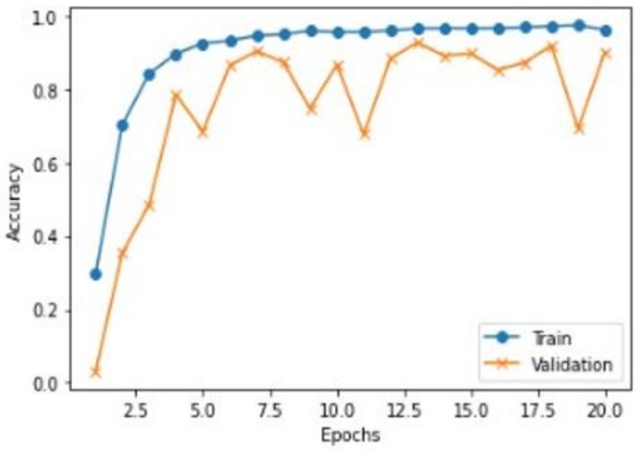

Figure 4: Accuracy Over epochs

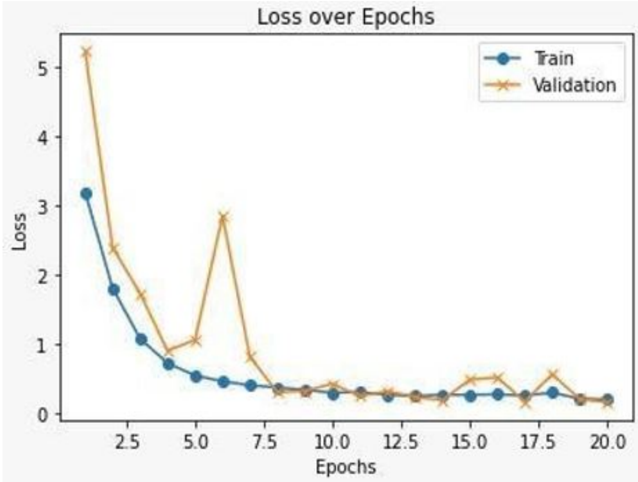

Figure 5: Loss Over epochs

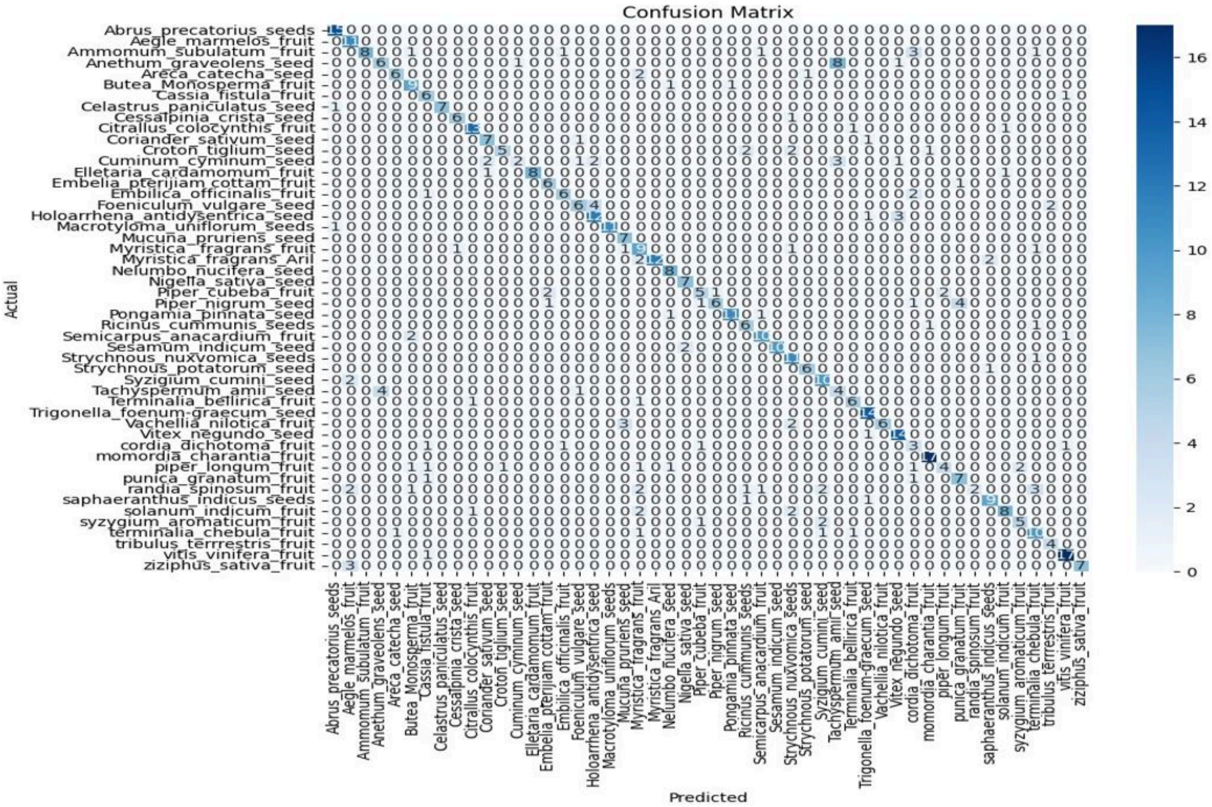

Figure 6: Confusion Matrix

Visual Predictions and Model Confidence Analysis for Dry Herbs


Cassia_fistula_fruit
Predicted: Cassia_fistula_fruit
Confidence: 100.0%
Celastrus_paniculatus_seed
Predicted: Celastrus_paniculatus_seed
Confidence: 99.78%
Cessalpinia_crista_seed
Predicted: Cessalpinia_crista_seed
Confidence: 98.27%
Citrallus_colocynthis_fruit
Predicted: Citrallus_colocynthis_fruit
Confidence: 99.74%
Coriander_sativum_seed
Predicted: Trigonella_foenum-graecum_seed
Confidence: 61.24%
Croton_tiglium_seed
Predicted: Ricinus_cummunis_seeds
Confidence: 47.31%
Cuminum_cyminum_seed
Predicted: Coriander_sativum_seed
Confidence: 99.6%
Elletaria_cardamomum_fruit
Predicted: Elletaria_cardamomum_fruit
Confidence: 67.36%
Embelia_pterijiam cottam_fruit
Predicted: Embelia_pterijiam cottam_fruit
Confidence: 99.96%
Embilica_officinalis_fruit
Predicted: Embilica_officinalis_fruit
Confidence: 72.61%
Foeniculum_vulgare_seed
Predicted: Foeniculum_vulgare_seed
Confidence: 50.34%
Holoarrhena_antidysentrica_seed
Predicted: Holoarrhena_antidysentrica_seed
Confidence: 59.45%
Macrotyloma_uniflorum_seeds
Predicted: Macrotyloma_uniflorum_seeds
Confidence: 100.0%
Mucuna_pruriens_seed
Predicted: Mucuna_pruriens_seed
Confidence: 96.21%
Myristica _fragrans_fruit
Predicted: Myristica _fragrans_fruit
Confidence: 64.54%
Myristica_fragrans_Aril
Predicted: Myristica_fragrans_Aril
Confidence: 100.0%
Nelumbo_nucifera_seed
Predicted: Nelumbo_nucifera_seed
Confidence: 99.92%
Nigella_sativa_seed
Predicted: Nigella_sativa_seed
Confidence: 100.0%
Piper_cubeba_fruit
Predicted: Piper_cubeba_fruit
Confidence: 99.72%
Piper_nigrum_seed
Predicted: Piper_nigrum_seed
Confidence: 56.33%
Pongamia_pinnata_seed
Predicted: Pongamia_pinnata_seed
Confidence: 100.0%
Ricinus_cummunis_seeds
Predicted: momordia_charantia_fruit
Confidence: 42.14%
Semicarpus_anacardium_fruit
Predicted: Semicarpus_anacardium_fruit
Confidence: 100.0%
Sesamum_indicum_seed
Predicted: Nigella_sativa_seed
Confidence: 50.74%

Figure 7: Confidence Score of Drugs used in the Project.

Conclusion

The CNN model developed for the identification of dry Ayurvedic herbs (fruits and seeds) demonstrated promising potential, achieving a peak training accuracy of 91.86% and validation accuracy ranging between 81% and 83%. This performance highlights the model's capability to extract meaningful features for herb classification. However, misclassifications were observed, particularly among visually similar herbs, indicating areas for improvement. The architecture's inference time of 36 milliseconds per step and robust performance on distinct herb species suggest its practical applicability for real-time herb identification. Despite its effectiveness, the model's generalization issues underline the need for further refinement. To enhance the model's robustness and scalability, several recommendations are proposed. Expanding the dataset to include diverse species, plant parts, and variations in drying and processing conditions, alongside capturing images from multiple angles and lighting conditions, could improve generalization. Addressing class imbalances through augmentation or resampling strategies and optimizing hyperparameters like learning rate, batch size, and dropout rate could mitigate overfitting. Additionally, incorporating advanced regularization techniques, such as L2 regularization or early stopping, and leveraging enhanced computing systems, including GPUs or TPUs, could further refine the model's performance. Implementing cloud-based platforms for distributed training and applying efficient pre-processing techniques like noise reduction and contrast enhancement would also contribute to more accurate classifications. These enhancements would establish a reliable framework for quality assurance in herbal medicine, fostering advancements in the identification and utilization of *Ayurvedic* herbs.

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