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Survey and Analysis of Medicinal Plant Identification via Image Processing and Machine Learning Techniques

Mr. Suraj Kachate [a], Ms. Diksha Nimgade [b], Ms. Gayatri Ambatkar [c]

[a] *Student, AGPCE, Nagpur, 441108, India*
[b] *Student, DBACER, Nagpur, 441110, India*
[c] *Student, TGPCET, Nagpur, 441108, India*

A B S T R A C T

The identification of India's vast array of medicinal plants, crucial in Ayurvedic medicine, remains challenging due to their diversity, seasonal variations, and morphological similarities. This issue results in market discrepancies and compromises product quality, raising skepticism about Ayurvedic remedies. To combat this, advanced image processing and machine learning algorithms such as GoogLeNet, R-CNN, and YOLO, along with libraries like TensorFlow, OpenCV and Detectron2, are explored for real-time plant identification. This survey assesses their effectiveness and identifies optimal datasets from reputable sources for training models dedicated to medicinal plant identification. Leveraging these technologies holds the promise of enhancing accuracy in identifying medicinal plants, benefiting Ayurvedic Pharmaceutics' supply chain stakeholders by addressing market confusion and ensuring product quality and authenticity.

Keywords: Plant Identification, Deep Learning, Neural Network, Medicinal Herbs, Image Processing, Machine Learning

1. Introduction

Medicinal plants have played a pivotal role in traditional healthcare practices across civilizations, spanning centuries. In contemporary times, a substantial population in developing nations continues to rely on these natural remedies, sourced almost freely from nature. India stands as a testament to this reliance, boasting a robust healthcare system deeply rooted in classical medicinal practices like Ayurveda, Siddha, Unani, and Swa-rigpa[20], complemented by diverse folk healthcare traditions. However, the effectiveness and reliability of these medicinal practices are often hampered by challenges in identifying the vast array of medicinal plant species. With an estimated 7,000+ species in India alone[19], the task of accurate plant identification becomes formidable due to their diversity, morphological similarities, and seasonal variations.

This challenge in plant identification has led to market discrepancies, compromising the quality and authenticity of Ayurvedic remedies, thus raising skepticism among consumers. To address this issue, there's a growing interest in leveraging cutting-edge image processing and machine learning algorithms as potential solutions. Techniques such as GoogLeNet[2], R-CNN[12], FRCNN[13], DPM[18], and YOLO[11], coupled with libraries like TensorFlow[15], OpenCV[16], and Detectron2[17], have emerged as promising tools for real-time plant identification. The primary objective of this survey is to critically assess the efficacy of these advanced algorithms and identify optimal datasets sourced from reputable repositories for training specialized models dedicated to medicinal plant identification.

The focal point of this investigation is to bridge the gap between traditional medicinal practices and technological advancements. By incorporating sophisticated algorithms and utilizing well-curated datasets, we aim to enhance the accuracy and efficiency of identifying medicinal plants. Our goal is to address prevalent challenges faced by stakeholders in the Ayurvedic Pharmaceutics supply chain, mitigating market confusion and ensuring the authenticity and quality of herbal products.

In this comprehensive survey, we delve into an in-depth exploration of various algorithms, including GoogLeNet[2], FRCNN[13], RCNN[12], DPM[18], and YOLO[11], assessing their capabilities in accurately identifying medicinal plants. Furthermore, we investigate the potential of using libraries such as TensorFlow[17] and OpenCV[15] to optimize these algorithms for efficient plant identification. Notably, we examine existing datasets meticulously compiled by esteemed entities like the Botanical Survey of India[8] and various other authors, as well as datasets available on platforms like Kaggle[9]. Additionally, we present findings from studies utilizing RCNN[12] and FRCNN[13] algorithms, achieving promising identification accuracies of up to 90%. However, to further improve accuracy rates, our research pivots towards exploring real-time detection algorithms like the latest versions of YOLO[3]. Moreover, while GoogLeNet[2] demonstrates commendable accuracy on mobile devices, our endeavor is to augment its performance further.

This paper comprehensively explores and evaluates the conversgence of traditional medicinal practices with cutting- edge technological solutions. By elucidating the potential of image processing and machine learning in the realm of medicinal plant identification, this survey seeks to pave the way for a more robust and accurate system benefiting healthcare practices reliant on herbal remedies.

2. Literature Review

[2.1] A Smart Study on Medicinal Plants Identification and Classification using Image Processing Techniques[1].

The research paper conducts a survey on various preprocessing techniques such as Gabor Filter[1], Median Filter[1], etc. It compares their advantages and disadvantages to determine their efficacy. Additionally, the paper explores segmentation techniques, including Edge detection-based[1], Threshold-based[1], etc. elucidating their respective strengths and weaknesses. Furthermore, it delves into feature-based extraction methods like Color- based features such as Histogram Intersection[1] Method and Color Histogram[1], as well as Shape-Based Features like 2D FFT[1], Earth Moving Distance[1], and various Region-Based image segmentation methods. It scrutinizes Classification methods like Probabilistic Neural Network (PNN)[1], K-nearest neighbor (KNN)[1], Fuzzy-based PNN[1], Convolutional Neural Network (CNN)[12] etc. The analysis indicates that CNN[12] demonstrates improved accuracy but with longer training times compared to other methods. These classification approaches vary significantly in their methodologies, employing neural networks, fuzzy systems, fractal measurements, and deep learning architectures to classify plants based on diverse sets of features and image datasets. However, there is a clear need for further development to enhance both the speed and accuracy of these results.

[2.2] Mobile-based Assistive Tool to Identify & Learn Medicinal Herbs[2].

The process of flower identification typically involves segmentation, feature design, pre-processing, and classification. Convolutional Neural Networks (CNNs)[12] have been successful in object detection, utilizing methods like mean-shift algorithm[2] for segmentation. Handcrafted features such as color, shape, and textures, along with techniques like Chan-Vese segmentation[2], are used for flower and leaf identification. Some studies focus on leaf identification using morphological features and various neural networks like Shallow NN[2], DBN[2], and RBF[2]. For leaf identification, image processing, feature extraction, and classification phases are employed. CNN[12] models achieved high accuracy ranging from 89% to 96% when tested on 1500 images of endemic plants. The best performing model for flowers and leaves datasets was Faster Region Convolutional Neural Network (FRCNN)[13], with a training set correctness of 100%.

[2.3] Identification of Medicinal Plants by Visual Characteristics of Leaves and Flowers[3].

The trained neural network model underwent testing on the test set to determine its classification accuracy, which varied based on the regularization parameters to optimize model characteristics. The obtained training set accuracy was 100%, depending on the number of epochs used. Test set accuracies ranged between 95% to 99% when assessed on 500 images each from 10 rare medicinal plants. The research proposed a robust CNN-based[12] technique for identifying rare medicinal plants, achieving a 90% test accuracy using TensorFlow[17] on a self-created dataset. This accuracy was attributed to extracting relevant leaf image characteristics and utilizing neural networks for model recognition, with accuracy improving as the number of epochs increased.

[2.4] You Only Look Once: Unified, Real-Time Object Detection[5]

Object detection systems historically repurpose classifiers to identify objects in images. Approaches like sliding window methods (e.g., DPM[18]) or region proposal methods (e.g., R-CNN[12]) are slow due to their multi-step processes. However, YOLO[5] (You Only Look Once) simplifies this by using a single neural network to predict bounding box coordinates and class probabilities directly from image pixels. It operates at high speeds (45 frames per second) and outperforms real-time systems, achieving over twice the precision. YOLO[11] considers the entire image for predictions, encoding contextual information, and making fewer background errors compared to other techniques like Fast R-CNN[13]. Despite its speed, YOLO[4] may struggle with precise localization of small objects, falling slightly behind in accuracy when compared to state-of-the-art systems.

[2.5] Medicinal Plant Database[8]

The Botanical Survey of India[8] has curated a comprehensive and dynamically updated database named "Medical Plant Database of India,"[8] accessible freely through their website. This database holds significant value in the realm of medicinal plant research and training image prediction models. With a meticulous compilation of information, it includes the scientific names, families, common names, herbarium images, and detailed uses of various plants. This resource proves invaluable in understanding the rich diversity of plant species employed across different medicinal systems in India, showcasing the country's substantial contributions to herbal medicines. Notably, it encompasses traditional practices like Ayurveda and Siddha, along with modern drug discovery and pharmacological research. The initial phase of this database encompasses 1,915 species[8], with ongoing plans to add an additional 1,000 species in subsequent updates. However, it's imperative to note that due to its dynamic nature with weekly updates, there is no archival version available. Therefore, users are encouraged to personally retain or store any cited or utilized data from this continually evolving and invaluable repository of medicinal plant information.

3. Methodology

This section describes the different image processing and machine learning technique used by authors to recognize the medical plants.

3.1 Mobile-based Assistive Tool to Identify & Learn Medical Herbs[2]

The plant identification mobile app uses TensorFlow[17] for classification, integrating machine learning models via Python's front-end API. It employs the Fast Region Convolutional Neural Network (FRCNN)[13] model to process images through a Convolutional Neural Network (CNN)[12], segmenting them into regions for plant classification. A region proposal network identifies object proposals with an objectness score, followed by standardizing sizes using a Roi pooling layer. The final fully connected layer with softmax[2] and linear regression[2] outputs object boxes. The app provides users with 3D models and descriptions of identified plants, and also supports plant searches through a virtual assistant without capturing images directly.

3.2 Mobile- Identification of Medicinal Plants by Visual Characteristics of Leaves and Flowers[3]

The proposed system utilizes Convolutional Neural Networks (CNNs[12]) to identify and classify rare medicinal plants based on images of their leaves. The process begins with the collection of image data from a botanical garden. Using CNN[12] as shown in figure 1, a model is trained on these images, employing convolutional layers[3] with 3x3 masks to extract features from the input images. Despite potential feature neglect, this method ensures higher accuracy by identifying maximum value pixels through continuous mask application. The trained images are stored in a database for plant identification. During testing, the trained images are used for predictions, facilitating the accurate identification of these medicinal plants. The system's accuracy is influenced by the quantity of images and epochs employed in training, with higher epoch numbers between 40-60 yielding improved accuracy levels.

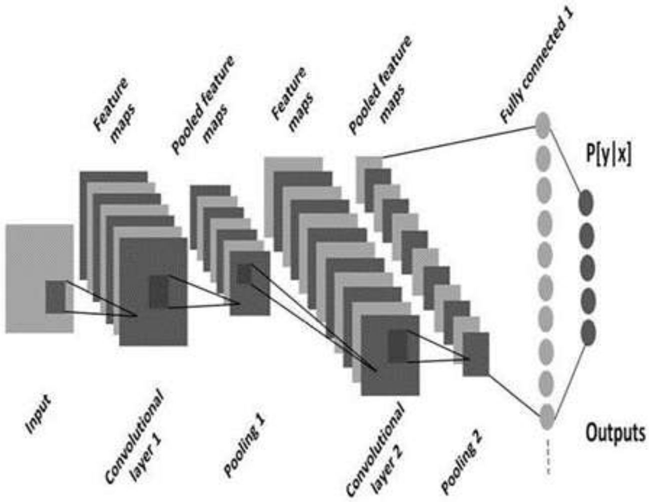

Fig. 1 - Convolutional Layers[3]

3.3 You Only Look Once: Unified, Real-Time Object Detection[5]

YOLO[11] redefines object detection by framing it as a regression problem, predicting bounding boxes and class probabilities directly from full images in a single neural network evaluation. The architecture of the YOLO[11] is shown in Figure 2. This unified architecture is exceptionally fast, with the base YOLO[11] model processing images at 45 frames per second in real-time. Even a smaller version, Fast YOLO[11], achieves an impressive 155 frames per second while doubling the mAP of other real-time detectors[4]. Although YOLO may make more localization errors, it significantly reduces false positives on background compared to other state-of-the- art detection systems. Moreover, it excels in learning general object representations, outperforming methods like DPM[18] and R-CNN[13] when transitioning from natural images to other domains such as artwork[5].

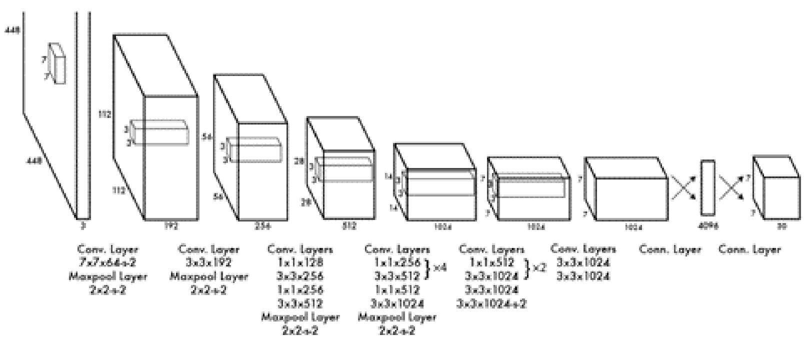

Fig. 2 - Convolutional Layers[3]

4. Analysis

Comparison between Detection Algorithms[5]

4.1 Deformable Parts Models (DPM)[18]:

YOLO[5] replaces DPM's[18] separate pipeline for object detection with a single neural network. It handles feature extraction, bounding box prediction, suppression, and reasoning all at once. YOLO's[11] approach, training features in- line, leads to a faster, more accurate model compared to DPM[18].

4.2 R-CNN[12]:

R-CNN[12] uses complex pipelines and region proposals, taking over 40 seconds per image. YOLO[5], similar to R- CNN,[12] proposes boxes using grid cells with convolutional features but reduces multiple detections by imposing spatial constraints. YOLO[5] suggests fewer boxes (98) than Selective Search (2000), combining all components into a single optimized model.

4.3 Other Fast Detectors[4]

Fast/Faster R-CNN[13] enhance R-CNN[12] with shared computation and neural network proposals but lack real-time speed. DPM[18] optimization efforts fall short for real-time, except for 30Hz DPM[18]. YOLO[5] ditches traditional pipelines for speed and versatility, detecting multiple objects unlike specialized detectors for single classes.

5. Conclusion

The survey delves into the multifaceted realm of medicinal plant identification, emphasizing the challenges posed by the vast diversity and morphological similarities among India's medicinal flora. Recognizing the significance of accurate plant identification in Ayurvedic medicine, the survey extensively explores various cutting-edge technologies and methodologies, including YOLO[11] for real-time detection, diverse image preprocessing techniques, and models like GoogLeNet[2] and R-CNN[12].

The pursuit of leveraging advanced image processing and machine learning algorithms, complemented by libraries such as TensorFlow[17], OpenCV[15] and Detectron2[16], holds immense potential in addressing the persistent challenges faced in the identification of medicinal herbs. By meticulously assessing the effectiveness of these technologies and identifying optimal datasets from credible sources for model training, the survey endeavors to enhance the accuracy of medicinal plant identification.

Ultimately, the adoption of these sophisticated technologies promises to play a pivotal role in mitigating market discrepancies, fostering authenticity, and ensuring the quality of Ayurvedic remedies. This transformative potential extends to stakeholders within the Ayurvedic Pharmaceutics supply chain, providing a pathway to tackle skepticism and confusion while bolstering confidence in the authenticity and efficacy of medicinal plant-based products. As a result, the integration of these advanced technological solutions stands poised to revolutionize the identification and utilization of India's rich repository of medicinal plants, benefiting both the industry and consumers alike.

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