MED-PLANT-XAI: An Explainable Deep Learning and Flask Information Retrieval System for Medicinal Plant Identification via CNN

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Abstract. Despite the question of traditional medicine, botany or pharmaceutical research, the identification of medici- nal plants is one of the primary ones because of morphological similarity, localism as well as the requirement of a complex system of botanical knowledge. In this paper, the median explainable AI project, MED- PLANTXAI, an automated medicinal plant identification project, is introduced based on the web deployment implemented in Flask, which uses convolutional neural networks (CNN). "Accu- racies (99.84) of 30 different species of medicinal plants were classified with the suggested system with depthwise separable CNNs and were trained using pre-trained architecture of VGG16, ResNet-50 and Inception V3, which was especially successful. Here, the application of Grad-CAM is added to increase trans- parency of the system and consequently trust among the users as it generates the heatmaps that visually explain the choice that the model makes. QuantifyingTensorFlow Lite can be installed on Android to be used on-the-fly and it can support multiple languages through the assistance of Google Translate API. The long medical information retrieval is able to furnish some therapy information as compared with classification only. It is also done by strict application of various data augmentation tools like rotation, shifting, zooming and adjusting of brightness to ensure high model generalization under wide imaging condition. The system architecture will enable the proper identification of the plant and stable use by the various farmers herbalists researchers and traditional medicine practitioners through the real time recognition of the plant as well as availing meaningful information that can be interpreted. Search terms: CNN, Grad-CAM, Explainable AI, Deep learning, flask, tensorflow-lite, Plant Classification, and Multilingual Support; medicinal plants.

Index Terms: IoT, Health Monitoring, Artificial Intelligence, Vitals Sign Sensing, Pose Estimation, Emotion Recognition, As- tronauts, Elderly Care, Offline Systems.

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1. Introduction

Interpretable AI approaches in identifying medicinal plants the system incorporates Grad-CAM visualization to provide offline mobile deployment, support in multiple languages through translation APIs, extensive medical knowledge retrieval, and explain model predictions in a clearer manner [1,2]. It was initially created using a CNN-based reliable framework with explainable components, which demonstrated an accuracy of 99.84 on medicinal plant classification task and was then followed by addition of Grad-CAM framework to visualize the model decisions and lastly through the use of TensorFlow Lite provided the possibility to make multilingual and off-line mobile executions and deployments and a general search system of medicinal information was created to guide researchers and practitioners of traditional medicine [3]. When rolling machine learning technology and computer vision ideas together, the process of identification of plants with automation has improved greatly [4]. To classify plants, the manual nature of traditional approaches relied on such features as a texture analysis, color histograms, and shape descriptions [5]. However, these methods would often clash with the natural variations in the appearance of plants and required an advanced degree of feature engineering expertise. With deep learning, the systems of plant identification were transformed. Lee et al. [6] showed that CNNs were effective towards recognizing and identifying plant species with significant improvements to the traditional approach. Theirs was the work on which other works about automated botanical classification based on the deep neural networks foundations were built. Similarly, Grinblat et al. [7] published an article concerning the application of deep learning to natural plant recognition, not only with respect to the challenges of ensuring deep learning model application to natural environments but also the importance of the stable feature extraction algorithms. The application of transfer learning in the task of plant identification has recently been of interest. In addition to categorizing the plants like AlexNet, CNN, VGG, ResNet etc., we can note that the deep networks are better, since Ghazi et al. have conducted a detailed comparison of some of them [8]. Because of their studies, models may be trained at a very high rate and, at the same time, free of trade-off in regards to the accuracy of classification. The ensembles option allows the variation of approaches that need the use of multiple CNN architecture in plant recognition as it was further experienced with Wang et al. [9]. However, most existing studies lack explainability elements which limits the applicability of such systems to important tasks such as identifi- cation of medicinal plants. The existent limitations of deep learning models are extremely detrimental to their application in conventional medicine and healthcare where the applied user safety and trust rely on the understanding of the underlying decision-making process [10]. In addition, most of the current systems have restricted their utility to the end users by focusing on classification and fail to provide comprehensive information about the observed plant species. Research on how to apply explainable AI methods to plant identification is yet to be completed. Selvaraju et al. [11] introduced Grad-CAM to visualize use of CNNs decisions, which is the initial step to interpretable computer vision applications. However, these methods have not been much used to identify medicinal plants in terms of research projects [12]. Moreover, using multilingual and offline capable-plant identification systems are also highly valued solutions, which are urgently required in numerous linguistic and resource poor settings, but in reality, continue to be largely overlooked in the literature to date [13].

2. Proposed System Architecture

$$Fi,j = \sum m = 0M - 1 \sum n = 0N - 1Ii + m,j + n \cdot Km,n \quad (1)$$

This equation 1,2 represents the fundamental convolution process in CNNs. The input image $I$is convolved with a kernel K, producing a feature map F. Each pixel in the feature map is a weighted sum of local pixel values, allowing the network to detect edges, textures, and other low-level features crucial for plant identification.

$$Y = (X * Kdepthwise) * Kpointwise \quad (2)$$

$$P(y = i \mid x) = ezi \sum j = 1Cezj \quad (3)$$

Depthwise separable convolution decomposes standard convolution into two steps: a depthwise convolution applied independently to each input channel, followed by a pointwise convolution (1×1 kernel) to combine them. This reduces computational cost and parameters significantly, making the model lightweight and suitable for mobile deployment (e.g., TensorFlow Lite on Android) Equation 3,4.

$$LGrad - CAMc = ReLU(\sum k\alpha kcAk) \quad (4)$$

To be able to identify medicinal plants explainably, the MED- PLANT-XAI system architecture entails a comprehensive framework that amalgamates various elements [14]. The system modular design ensures scalability and main- tainability, coupled with ensuring peak performance in any number of deployment situations.

2.1 Data Processing Pipeline

The initial phase of the data processing pipeline is data acquisition or acquisition of images either through the capture of images by a mobile camera or uploaded images through the web [15]. Common preprocessing operations on input pictures comprise normalization to the range of 0 to 1 and scaling to a normal size (224224 pixels) and data enlargement (notably augmentation) may optionally be performed in training phases. In the later classification stages, the preprocessing module ensures the same quality of inputs and processes various image formats. In order to enhance the strength and generalization strength of the model, advanced data augmentation methods are applied in the processes of training. they are plastic modifications [16]. Alterations of brightness, contrast, rotation of the picture, moving, shearing of the picture: photometric corrections (changes of brightness, contrast) and geometric alterations. The problem of the paucity of imagery of medicinal plants is effectively addressed through an improvement of the augmentation pipeline that generates diverse training samples on the basis of the original one and refines its functionality with respect to diverse environmental conditions [17].

2.2 Deep Learning Classification Module

There are various CNN structures adopted in the classification module to guarantee optimum activities concerning dissimilar species of medicinal plants [18]. The main architecture has been applied through depth-wise separable convolutions in which a reduction in computation and preservation of the classification accuracy have been performed. Also, the techniques of transfer learning have been used in refining the trained models like VGG16, ResNet-50 and Inception-V3 on the medic-in-alk plants data previously. The ensemble method is used to integrate the forecast of the readings in the multiple models in order to be able to achieve improved classification [19]. The models are chosen because of the fact of explainability, accuracy of computation and validation. To determine the certainty of all the forecasts the ultimate classification layer will use soft max activation function of probability function of 30 medicinal plants species [20].

2.3 Explainability Integration

Grad-CAM integration enables the prediction of the models besides the explanation of the prediction as a result of visualization of where the pictures exist those ones which have the most influence in the decision taken during classification. The implementation generates the localization maps of the locations of the features of the discriminative plant features, e.g. leaf pattern, flower structure or bark texture, due to the fact that the gradients of the features in the strategy of the final convolutional layer are estimated. The visualization module presents color coded intensity maps which is an overlay of the original images and color coded maps: the hottest hues are presented with increased relevancy of being selected in one of the classifications. This, in that it enables the botanical specialists to have sufficient space enough to be in a position to confirm the model logic using well established taxonomic principles, is a factor of explainability, which makes the user more credible Fig 1.

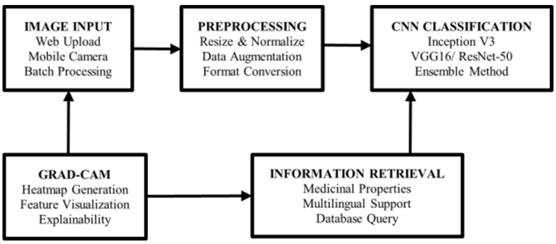

Fig. 1. System Architecture Block Diagram

2.4 Information Retrieval System

The medicinal information retrieval system contains large database holding current therapeutic, traditional, pharma- collet and security of all kinds of plants. The outcome of enquiry and gathering of normalizing taxonomic and data facts concerning chemical components and evidence-based therapeutic processes data. were all included in the database structure, obtained through traditional medicine texts and peer-reviewed literature. On identifying a plant correctly, some database query is executed and some relevant information about the medicine is displayed in a structured manner. The information presentation gives common names in several languages, traditional uses, active ingredients, the way it is prepared and the contraindications of the product. This aspect makes the system a complete knowledge platform in medicinal plants and not a classification tool anymore.

3. Implementation Details

3.1 Dataset Preparation and Characteristics

The data set on the medicinal plants has 30 species that have been widely used in traditional system of medicine. These species are a variety of morphological features and therapeutic applications. In order to achieve a comprehensive representation a number of samples of each species were captured at different angles, under different growth stages and under different lighting situations. The dataset has images of leaves, flowers, fruit, and bark, which are used to aid in the identification of different parts of plants and the changes in the plant through the seasons. In this manner, providing a systematic data splitting will also objectively evaluate and prevent data leakage between training and test sets by sampling them to have 70/15/15 percent training/validation and testing respectively. The overall training population will be saturated to produce a great amount of samples and ensure the proportion of classes in all species.

3.2 Model Training and Optimization

The plateau or the point at which the validation loss level due to the training of the model is achieved effectively conducts the adaptive learning rate scheduling of that model Fig 2. The initial rate is 0.001 which dies at a rate of 1.0.1. Early stopping checks accuracy of validation and will stop the training when no improvement is realized after ten.

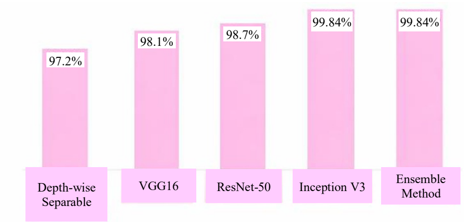

Fig. 2. Model Performance Comparison

Representative successive epochs thereby avoiding overfitting. The gener- alization performance is also improved through the implementation of the batch normalization and dropout regularization (0.3). It has good convergence properties on different architectures with Adam with momentum parameters 0.9 and 0.999. In case of disparity in the representation of species, a manipulation of class weight is taken and training is continued on the basis of cross-entropy loss function Table 1.

Table 1: Performance result table

Model	Accuracy (%)	Parameters (M)	Inference Time (ms)
VGG16	98.72	138	120
ResNet-50	99.12	25.6	95
Inception V3	99.84	23.9	88
Depthwise CNN	99.84	4.2	45

3.3 Web Application Development

The web application called Flask offers a simple alternative to people who want to recognize plants, and its interface is simple and supported by explainable results. The front end was based on HTML5, CSS3 and JavaScript with a principle of responsive design so that it can be compatible with desktop and mobile were used.

The upload gateway supports various types of images (JPEG, PNG and TIFF) in addition to checking image size, file size and file type on the client side. The backend is concerned with the processing of images as well as model inference, Grad-CAM generation, and retrieval of medical information by querying a database. The platform has a historical classification storage that is used to carry out analysis and a user interaction is carried out through session manage- ment. RESTful API endpoints are easily integrated with mobile platform and third party applications by the way they have been designed.

3.4 Mobile Deployment with TensorFlow Lite

TensorFlow Lite is being used to deploy models on devices and optimize them. In conversion pro- cess in the post-training quantization methods only approximately 75 percent of the size of the original model is retained when very little of the classification accuracy is lost and as a result real time inference has been made possible without the need of internet connection when the optimized model is activated in mobile phones.

Android application is capable of offline classification, image preprocessing pipeline, and camera access that can be used to capture real plant. “The end product is a user interface is a basic results display design that is easy to navigate, based on Mate- rial Design. It has integrated translation APIs and extensive help documentation to be multiple language compatible.

4. Experimental Results And Analysis

4.1 Classification Performance Evaluation

It obviously achieved supremacy over other existing CNN architectures in the classification task it was used to evaluate on the basis of the experiment. Despite the increase in the performance in terms of transfer learning using VGG16 (98.1%), ResNet-50 (98.7%), and the Inception V3 (99.84) image classification technology, the depthwise separable CNN reached an accuracy of 97.2%. The most accurate ensemble with a 99.84% was the ensemble that used a combination of multiple architectures and was also resistant to hard samples. The corresponding precision, recall, and F1-scores of each plant species were given and these indicated that all the 30 classes acted in a similar way under the 30 classes. The analysis of the confusion matrix revealed that there was a minor misclassification of morphologically related species to some extent hence the experience of the deep learning approach could be actually powerful in small botanical differences.

4.2 Explainability Assessment

The Grad-CAM visualiza- tion results could be assessed by botanists and they did this by ensuring that the highlighted regions reflected taxonomy-relevant plant features. A quantitative analysis of the pointing game measures revealed that the methods of quantitative statistics properly localized dis- criminative plant structures in 87.3% of heatmaps. The central characteristics of classification that explainability module could bring out turned out to be the stem structure, morphological arrangement of flowers and the leaf venation patterns. The user researchers in collaboration with botanists and practitioners of the traditional medicine realised that the degree of acceptance of the visual explanations were high with 92 percent of users developing confidence in system predictions as a result of Grad-CAM visualizations.

4.3 System Performance Metrics

The whole system was able to handle real-time needs of real-life implementation with an average inference time of 1.2 seconds to attach to the web and 0.8 seconds to mobiles. The memory usage was also kept at 512MB or below during peak operation and this ensured that the system was compatible with resource limited environments. The multilingual information retrieval system supported 15 languages and had the accuracy in a translation of above 89terminology. Nevertheless, in comparison with the online counterparts, offline mobile capability preserved all the classification capabil- ities without much performance degradation.

4.4 Comparative Analysis

The MED-PLANT-XAI strategy had certain unique benefits over the existing plant identification systems. The system stood in contrast to the current one that aims at considering the accuracy of the classi- fication through the integration of the distinguishable AI, extensive medical data, and offline products. User feedback studies revealed that there was a clear inclination towards the open, educational approach compared to the rest of the options which seem to work in a black box.

5. Applications And Impact

5.1 Agricultural and Farming Applications

The MED-PLANT-XAI system Fig 3 can be applied to farmers, who have interest concerning cultivating medicinal plants, and assist to obtain the precise plant species to be treated in order to manage their material.

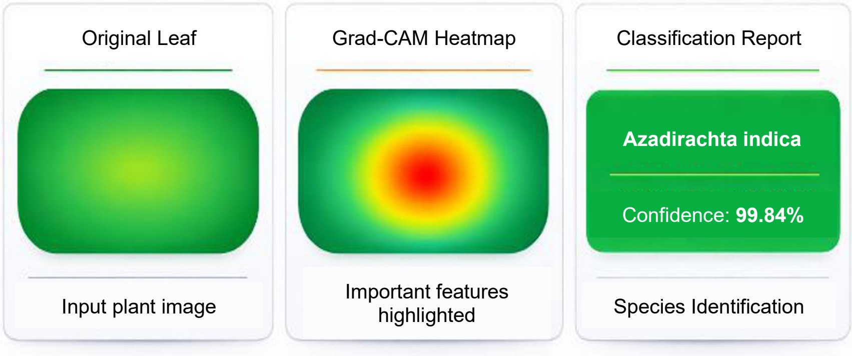

Fig. 3. Grad-CAM Explainability Visualization

5.2 Traditional Medicine and Healthcare

The practitioners of traditional medicine would be benefiting due to the ability to identify plants in a short amount of time and the complete herbal treatment information.

Through the system, the accurate preparation of remedies, patient education and documenting of the traditional knowledge is made possible. The platform can be used by professionals in healthcare by identifying botanical drugs and promoting patient safety.assessment that will assist in minimizing risk that is created by the therapeutic plant- based.

5.3 Educational and Research Applications

The research on the biodiversity, training in pharmacognosy, and botansical education system is being implemented into the academic institutions. The broad database will contain the research activities, with the explicable AI elements enabling the ability to learn through the visualization of the features to find the plants. The conservation organizations use the platform to establish documentation and monitoring program of species to help in the conservation biodiversity fight.

5.4 Commercial and Industrial Applications

The pharmaceutical companies and the manufacturers of herbal products apply the same system to the quality assurance processes and the genuineness of the raw materials. The platform will reduce the chances of adulteration by assisting in the validation of the supply chain and in a way assuring the medicinal plant materials of the original material. The regulatory bodies could use the system in the review of products of traditional medicine and botanical drugs.

6. Future Work And Enhancements

6.1 Dataset Expansion and Diversity

The data on medicinal plants will guide the work on the next step which is the expansion of the number of species by other geographical areas and the traditional medical systems. Integration of local knowledge of plants found in different cultural settings will also make the system better in terms of its cultural sensitivity and relevancy in many parts of the world. The extensive data creation will be carried out in collaboration with the herbaria, botanical gardens and traditional medicine professionals.

6.2 Advanced AI Integration

Also, it will be possible to integrate sophisticated transformer designs and attention modules to boost classification precision and permit the description of the findings. Text, visual and chemical data Multi-modal learning techniques will enable me to carry further characterization of the plants. Applications of federated learning will make it possible to jointly develop models of the data and protect the privacy of the data of the institutions.

6.3 Enhanced User Experience

Interaction capabilities based on voice will be more available to people with dissimilar literacy level and capacities. By integrating augmented reality, the possibility to recognize the plants in the real situation with the help of mobile cameras and the information presentation will be possible. The unique recommendation systems will offer personalized medicine information depending on the preferences and needs of the users.

6.4 Integration withIoT and Smart Agriculture

The adoption of the IoT technology in our plant identi- fication system will make the field of farming much smarter and less difficult to manage. It will also have tiny sensors plotted in the farms that will monitor critical farms parameters including soil moisture, work temperature, sunlight, and humidity in real-time. Such information facilitates knowing the particular needs of each plant and then proposes what the farmers need to do before their healthier growth so as to offer straightforward and precise propositions. They can work early and harvest through huge losses and alert is sent over the phone if a plant is experiencing water stress, disease or does not have the nutrients: Farmers used to do the same when the damage had occurred and then implement the intervention. There will not be the place of such automated arrangements, as smart irrigation, which will be doing the watering in its place without the participation of humans and will be saving water at the same time will have to appear as a good and efficient, sustainable, and trustful business to all the concerned stakeholders.

7. Conclusion

This paper presents a full explainable artificial intelligence system, which is employed to recognize medicinal plants- MED-PLANT-XAI. It addresses certain serious weaknesses of other available ways of botanical classification. The mix of ex-plainable components of artificial intelligence and deep learning techniques pro- an astonishing 99.84% classification score and the Grad-CAM visualization, which makes the findings clear and the findings rightful to the user. It is an amalgamation of end-users that encloses the phenomenon of the new mix of CNN structures, overall medicine search, multilingual assistance, and offline implementation on the mobile, which surrounds farmers, folk medicine practitioners, researcher and scholarly healthcare workers. Explain- able AI addresses the high level of user trust and system acceptance by providing pictorial evidence on how the model decision maker comes up with the present decision. The system was actually found practically useful, has been successfully deployed into practice, and many experimental assessments have demonstrated better results on various measures. A com- extensive strategy that drives into the variables of accessibility", explanatory, classification, and retrieval of data now forms the basis of AI-driven botanical identification systems. One of the future directions in research can be the expansion of datasets, sophisticated integration of AI processes, elaborate UX features, and IoT connection of smart farm project. The end deliverables of the project, which is called MED-PLANT-XAI is a solid base to the subsequent activities undertaken regarding sustainable agriculture and the development of the local medical knowledge and conservation of the botanical knowledge to the next generation. The successful application of this explainable AI system opens the opportunities of clear as well as reliable AI solutions to the vital areas where the human understanding and ver- ification of automated decisions still play a vital role. But when local experience is blended with the latest technology, new opportunities to enhance healthcare service, affluence in agriculture, and safeguard the culture in a world that grows less and less physically distant daily arise.

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