Identification of Medicinal Plants in Ardabil Using Deep learning

Conference Paper · May 2022

DOI: 10.1109/CSICC55295.2022.9780493

1 author:

Jafar Abdollahi
Islamic Azad University, Ardabil Branch

2022 27th International Computer Conference, Computer Society of Iran (CSICC), Tehran, Iran

Identification of Medicinal Plants in Ardabil Using Deep learning

Identification of Medicinal Plants using Deep learning

Jafar Abdollahi
Department of Computer Engineering, Ardabil Branch, Islamic Azad University
Ardabil, Iran
Ja.abdollahi77@gmail.com

Abstract— Ardabil is well-known for offering the ideal environment for a good, cheap medicinal herb. Various plant parts are used as essential components in producing natural medicines. According to IUCN (International Union for Conservation of Nature) records, many medicinal plants are on the verge of extinction, so employing image processing and computer vision algorithms to distinguish proof of medicinal plants is critical. As a result, the digitalization of beneficial therapeutic plants is critical for biodiversity preservation. The use of Convolutional Neural Network (CNN)-based techniques to distinguish Indian leaf species is investigated in this research. Several Deep Learning frameworks have recently been used to discern, identify, and characterize various plants. This study is mostly focused on identifying medicinal plants that can be found in rural areas. The Transfer Learning technique selected a well-known pre-trained CNN architecture called mobile net v2. The medical plant dataset was built using 30 different classes of medicinal plants, totaling 3000 photos, and these models were assessed with their pre-trained weights. On a held-out test set, the trained model had an accuracy of 98.05 percent, demonstrating the practicality of this approach.

Keywords— *Medicinal Plant, Deep learning, Identification, plants.*

I. INTRODUCTION

There are many different types of plants, all of them playing an important role in maintaining the earth's biodiversity by providing air and water to living humans [1]. Medicinal plants are plants used to treat and prevent certain diseases and conditions that affect humans [2]. There are many different types of herbal remedies, and they can vary from place to place, resulting in a similar pattern of "size" and "shapes" [3, 4].

Automatically identified and classified medicinal plants are a lively study area within image handling. The critical steps in determining medicinal plants and classification processes, which affect the organization's accuracy, are feature extraction and classification. Good knowledge of plants is important to improve the balance of the environment in identifying new or rare plant species [5]. Due to these facts, many researchers have expressed a strong interest in the study of automatic medicinal plant recognition. There are several avenues for progress in developing a strong classifier that can reliably categorize medicinal plants in real-time [6].

There are thousands of medicinal plants available worldwide, many of which are endangered. Medicinal herbs treat cardiac illnesses, respiratory disorders, reproductive issues, gastrointestinal diseases, joint issues, dermatological diseases, excretory disorders, and other ailments. As a result, proper medicinal plant identification and preservation must be considered. Manual identification is cumbersome because it takes time and can be inaccurate or imprecise at the same time. Furthermore, many of those medicinal plants are found in areas where humans cannot reach them with their hands. It would be helpful to have an automatic recognition system to categorize medicinal plants in such a situation [25].

The Convolutional Neural Network (CNN) technique was utilized to identify medicinal plants and disseminate their leaves in this study. This paper will create a model for identifying medicinal plant leaves using CNN and training data distributed across a large computer network, which will then be implemented in mobile-based software to recognize the different types and benefits of medicinal plant leaves discovered. Several examples of pictures are shown in Figure 1.

Achille millefolium | Actaea racemosa | Aesculus hippocastanum

Fig 1. Sample images

II. LITERATURE SURVEY

Plant identification is difficult and necessitates a thorough understanding of the subject and extensive expertise. Furthermore, the number of researchers capable of identifying medicinal plants is limited. During plant identification in the field, the researcher must bring a book dictionary of plants [7]. This is since the community's use of medicinal plants is extremely low. As a result, we require a computer-assisted system to assist humans in identifying these distinct sorts of medicinal plants. Medicinal plants (herbs) are plants that have substances that are beneficial to one's health. Each portion of the medicinal plant is thought to contain different characteristics that can help prevent, treat, or even cure a specific ailment [8].

978-1-6654-8027-7/22/$31.00 ©2022 IEEE

The earlier plant identification method was suggested by H. X. Kanet al [9]. Reddit al [10] have extracted a unique collection of "Leaf Width Factor" features using the Flavia dataset with nine other moral characteristics. The methodology for the intelligent and precise identification of plants using the Artificial Neural Network (ANN) and various image processing techniques is proposed by Pushpa Bret al [11]. Sandeep Kumar et al. [12] proposed a new texture-based feature descriptor that uses different color image channels to extract more meaningful features and improve classification efficiency to classify medical plants automatically.

A. Convolutional Neural Network

The CNN is one of the most extensively used Deep Learning and neural network algorithms for processing visual image data. Experiments with CNN features and other classifiers have yielded consistent and high-quality results. CNN have two layers: Feature Learning and Classification using Backpropagation [8, 13-18].

The CNN is a deep learning model with numerous hidden layers that learn multi-class breast cancer's inherent laws and characteristics. Layer-by-layer, the CNN is designed as follows:

- Input Layer:

This layer loads entire plant pictures and generates outputs for the primary convolution layer. The input layer's goal is to resize the photos of the plants to 256 * 256 utilizing mean subtraction. Within the 8-bit depth of red-green-blue channels, the input images are made up of three 2D arrays.

- Convolutional Layer:

To extract features, this layer computes the output of neurons that link to local areas of the input layer or the preceding layer. The collection of convolved weights with the input is referred to as a filter or kernel. The scale for each filter is 3 * 3, 5 * 5, or 7 * 7. Within the preceding layer, each neuron is only weakly linked to the environment. The space between filter applications is referred to as the stride. The stride has a hyperparameter of roughly two, which is less than the filter size. The convolution kernel is applied in overlapping windows, starting with a 0.01 regular deviation distribution. Each of the 64 filters in the final convolutional layer starts with Gaussian distributions with a regular deviation of 0.0001. The values of all local weights are viewed as ReLU (rectified linear activation) [13-18].

- Pooling Layer:

The pooling layer reduces the size of feature maps by combining comparable feature points into a single point. Dimension reduction, noise reduction, and receptive field amplification are all required by the pooling layers. The outputs of the pooling layer are scale-invariant, which reduces the number of parameters. Because the relative locations of each feature are coarse-graining, the final pooling layer uses a mean-pooling technique with 7 X 7 receptive fields and a stride of one. With 3 X 3 receptive fields and two strides, the opposite pooling layers adopt the max-pooling strategy. Figure 2 depicts the basic phases of categorization using CNN.

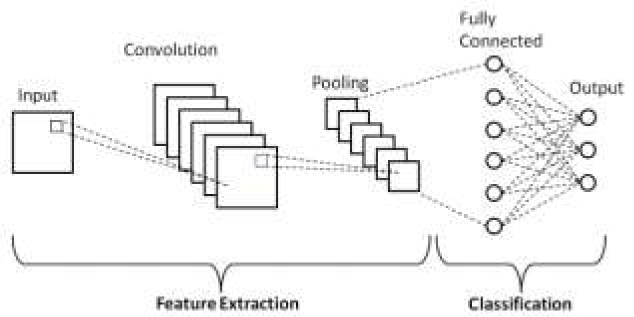

Fig. 2. Basic steps of classification using CNN

The input image's low-level features are extracted by the first convolution layer, while the successive layers extract semantic features. A kernel slides over the input to produce output using the dot product concatenated with bias in the convolution layer. It is activated with a nonlinear activation function, such as ReLU. The convolution layer's output is transferred to the pooling layer, which reduces the image's dimensionality while preserving the image's essential information. The image's high-level features are extracted using convolution and pooling layers. After that, the feature map is compressed into a one-dimensional vector and fed into a fully linked network. Multiple hidden layers with weights and biases are present in a fully connected neural network. To allow backpropagation, the neural network employs a non-linear activation function.

On the other hand, the linear activation function does not permit backpropagation because a part's derivative is unrelated to inputs. The neural network's performance will not improve with more hidden layers unless we employ a non-linear activation function. Finally, an activation function such as sigmoid or softmax is used to classify the item using a probability scale ranging from zero to one.

B. Feature Extraction

- Morphological Feature Extraction

There are two types of morphological features: basic and derivate. The diameter, area, and perimeter/leaf circumference were the primary characteristics used in this study. Eight derivate features, such as smooth, shape, ratio perimeter, diameter, and five-leaf vein features, can be obtained by combining three essential elements [7].

- Texture Feature Extraction

The Binary local pattern was created with texture description in mind. The operator adds a label to each pixel in a picture by multiplying the middle pixel value by the 3x3-neighborhood of each pixel and converting the result to a binary number. The label's histogram is employed as a texture descriptor [7].

- Shape Feature Extraction

To detect the edge of the leaf, this research used image thresholds and a Canny edge detector. The boundary of an object is detected using 4-connected neighboring [7].

C. Mobilenetv2

Classification of Images using MobileNetV2

The Deep Neural Network MobileNetV2 might be utilised to solve the classification challenge. TensorFlow was used to load pre-trained weights from ImageNet. To prevent the loss of previously learnt qualities, the bottom layers are frozen. Then, using the obtained dataset, additional trainable layers are added to see which attributes may be used to identify different types of medical plants. The model is fine-tuned after that, and the weights are stored. By allowing you to apply current biassed weights while keeping previously learnt features, using pre-trained models saves time and money [26].

II. PROPOSED METHOD

Plants are considered crucial since they are the earliest energy source for humanity and have nutritional, therapeutic, and other benefits. Medicinal plants are significant since they are one of the primary suppliers of medications. Cardiac disorders, respiratory ailments, fertility issues, and other diseases can all be cured. As a result, accurate identification of the medicinal plant is necessary for proper treatment. Manual recognition is not only inaccurate but also time-consuming. Automatic recognition for medicinal plants is suggested to avoid these concerns. The characteristics are derived from photographs of plant leaves that have been categorized. The form, texture, and color qualities are all taken into account. After that, deep learning classification algorithms such as mobile net v2 are employed to classify the data, comparing their results. All the simulations are wiped out google colab. The complete flow diagram to show the steps of the proposed method is shown in figure 3.

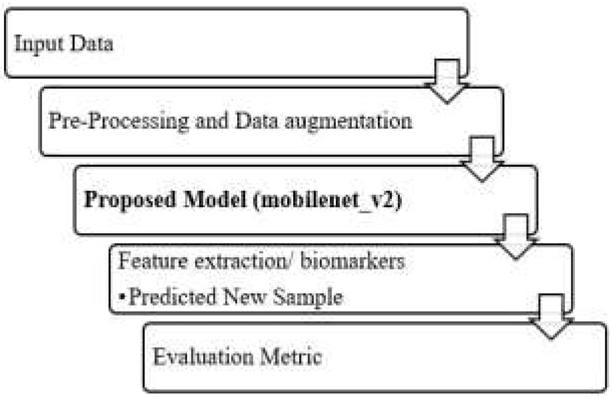

Fig 3. Show the steps of the proposed method

A. Database

Medicinal plant identification studies are frequently conducted using the researchers' databases. The medicinal plant database is collected from the source: https://github.com/Jafar-Abdollahi/medicinal-plants.

TABLE I. Describes the Sample Size Selected from each of the Datasets used in this Paper.

Dataset	Images	Class	Resolution
Medicinal Plant	3000	30	640 × 480

The images were randomly selected into separate sets with the following distribution: 75% for the training set amounting to 2400 images, 10% for validation amounting to 300 images, and finally, the remaining 300 images were allocated in the test set. Therefore, composing the dataset used in this work. Some of the sample images of the dataset are shown in figure 1. Hardware and software requirements are tabulated in Table II.

TABLE II. SOFTWARE REQUIREMENTS.

Distribution	Anaconda Navigator and Google Colab
API	Keras
Library	Tensor Flow, OpenCV
Packages	Matplotlib, NumPy, pandas, sci-kit learn
Language	Python 3.7
IDE	Jupyter Notebook
GPU Architecture	Google Colab
Applications	labeling, TensorBoard

B. Pre-processing

Pre-processing is taken into account, a really common process in computer vision applications. Pre-processing techniques are designed to stress the image aspect, which might help the popularity process or be useful within the deep learning training phase to eliminate unwanted noise. The preprocessing procedure applied to the pictures extracted from JPG files is as follows:

- Normalizing the pixel values of images.
- Cropping the images to remove any zero-valued pixels surrounding the images.

We transformed all of the photographs to the same size of 224 by 224 pixels because the information set is not uniform, and the images are of varying sizes. As a result of the RGB reordering, the final input to the proposed model is delivered as 224 224 3 pictures. It is worth noting that the data set is restricted. As a result, we used a 20-degree rotation range for the data augmentation. The JPG photos were flipped horizontally and vertically to expand the knowledge set considerably. This data collection is now ready to coach on more photos with the same data set.

C. Data Augmentation

Data augmentation is a technique that allows you to expand the amount of data you have greatly. As a result, augmentation techniques increase the number of class pictures to prevent the model from overfitting. Rotation and Gaussian blur are two data augmentation techniques used in this study.

D. Proposed Model

Innovation

The transfer learning method is utilized to educate a convolutional neural network in this article (CNN). This paper provides an upgraded convolutional neural network mobile net v2 algorithm based on deep learning to achieve this purpose. The methodology for detecting medical plants supported by photos that have been proposed is described. We have extended the architecture of the mobile net v2 family and used photos to train the models. The proposed method comprises image processing algorithms for detecting leaves and extracting significant leaf attributes for a few deep learning classifiers. When it comes to categorizing leaf images with typical plant traits, including shape, vein, texture, and several features, these deep learning classifiers are grouped based on their performance.

The steps taken to identify medicinal plants in the image processing technique are:

- The database of medicinal plants has been collected from the database of medicinal plants. The images collected are known as the machine input image.
- Input picture is pre-processed before application of classification techniques to eliminate noise, improve the section, and filtrate, cut, and resize pictures. In this stage, only interest sections of the image will be focused on, and irrelevant data will be eliminated from the image.
- The next step is to extract the characteristics from the original plant's pictures and feed the classification to recognize them. Features extraction and classification are achieved with a few shot image processing techniques.

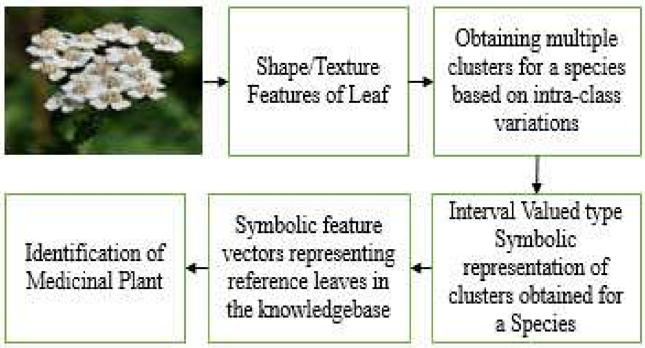

Fig 4. Proposed machine block diagram

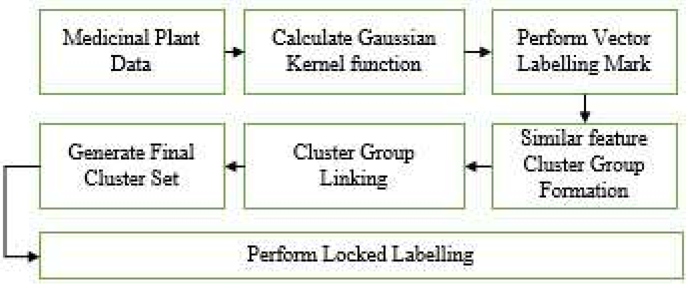

Fig 5. Proposed model architecture

The Proposed machine block diagram showed in figure 4, and the Proposed model architecture showed in figure 5. Also, the process of medical plant recognition is clearly explained in figure 6.

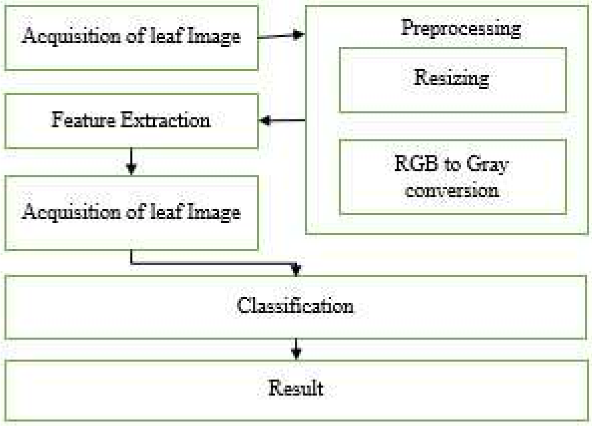

Fig.6. process of medical plant recognition

E. Performance Metrics

The performance of the deep learning-trained model on unseen data, referred to as a test dataset, must be assessed. The algorithm analysis will be influenced by the performance metrics chosen. This aids in identifying the causes of misclassifications so that corrective action can be taken [19-24, 29].

Accuracy: Indicate the class's number of "correct predictions made" divided by the number of "total predictions made" by the same category.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Sensitivity: If the person's result is positive, the model will be positive in a small percentage of cases, as computed by the formula below.

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Specificity: If the result is negative for the person, in a few percent of cases, the model will also be a negative result, which is calculated from the following formula.

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \quad (3)$$

Recall: The recall criterion expresses the ratio of the "number of correctly categorized text data" in a particular class to the total number of data categorized for that class.

$$\mathrm{Re}call = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (4)$$

Precision: Measures the ratio of the division of "correctly made predictions" for samples of a particular class to the number of "total predictions" for examples of the same class (this number includes the sum of all true and false predictions) [12-17, 29].

$$\mathrm{Pr}ecision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (5)$$

III. RESULT

Identifying good medicinal plants is challenging, and it is time to safeguard medicinal plants since several plant species have become extinct. Here we have proposed some way to extract shape, color, and texture features from leaf images and train an artificial neural network (ANN) classifier to spot the precise leaf class. The experimentation has been conducted on a medicinal plant leaf database of 3000 images with 30 images in each class. Features are computed for every of the 3000 medicinal leaf images. The performance measure for each classifier is calculated, which is presented in tabular and graphical representations. This experiment identified the respective medicinal plant leaves using performance accuracy due to the tool. The results of Accuracy and loss for training and Validation of the Mobile-net2 showed in figure 7, and the results of the predicted new sample showed in figure 8.

TABLE III. Result of Mobile-net2

Model	lr	Loss	Epochs	Loss	Accuracy	Val_Loss	Val_Acc
Mobilenet_v2	1e-3	Categorical Crossentropy	50	0.0310	98.67	0.6113	0.8305

Plants play a critical role in the conservation of natural resources. Plant species identification provides crucial information about plant categorization and attributes. Many plants have active therapeutic compounds and are high in medicinal components. Because of the requirement for mass production, the title of these plants is instantly required. Manual identification of medicinal plants takes time, and the assistance of plant identification experts is required. To tackle this challenge, humans must be able to recognize and classify medicinal plants automatically. Deep learning has outperformed other AI systems in various automated image-recognition applications. This research aimed to create and test a deep learning system that could identify medicinal plants.

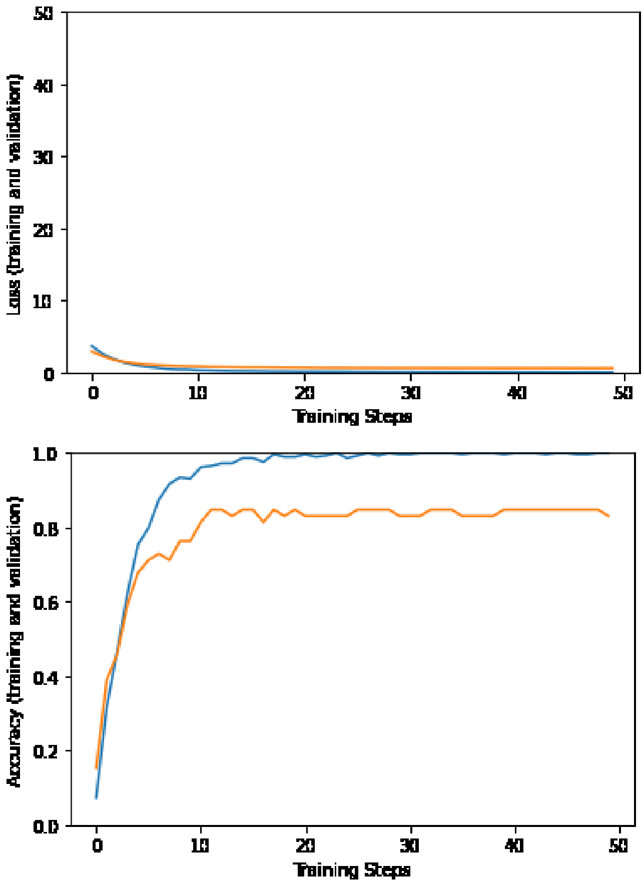

Fig.7. Result of Accuracy and loss for training and Validation of Mobile-net2

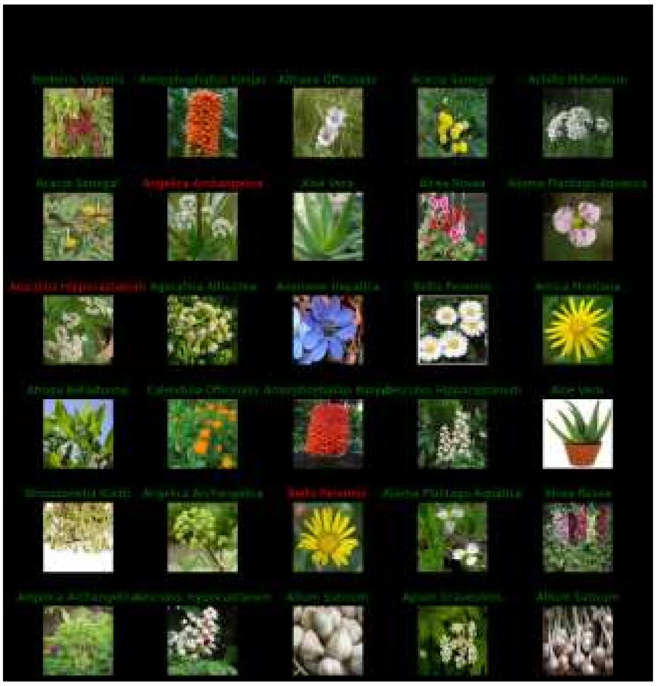

Fig.8. Result of predicted new sample

IV. DISCUSSION

Medicinal plants are significant since they are one of the main sources of medications, yet identifying them quickly is still difficult due to a lack of critical infrastructure. Growing smartphone adoption worldwide and recent breakthroughs in computer vision enabled by deep learning have paved the path for smartphone-assisted plant identification. We trained a deep convolutional neural network to detect 30 plants using a public dataset of 3000 photos of medicinal plants collected under controlled conditions. On a held-out test set, the trained model had an accuracy of 98.05 percent, demonstrating the practicality of this approach. Overall, training deep learning models on increasingly huge and publicly available image datasets offers a clear route for global smartphone-assisted crop disease diagnosis.

Herbalism makes extensive use of medicinal herbs to investigate their medical characteristics. This paper aims to use neural networks to create a computer-aided system for leaf medicinal plant identification. This technique uses computer-aided design to assist taxonomists in automatically spotting leaf medicinal plants. This method employs three-leaf characteristics: morphology, shape, and texture to identify the medicinal plant. Because it is easy to find, the leaf is employed in this approach for identification.

V. CONCLUSION

Artificial intelligence has been successfully used in large data systems to facilitate analytics and knowledge discovery by recognizing hidden and intricate patterns [27, 28]. Each plant is said to be medicinally sound based on historical evidence. Humans must first determine which part of the plant has a medicinal benefit for the condition. Experiments revealed that using a combination of leaf traits to identify medicinal plants improves accuracy by 98.05 percent. A statistical comparison of leaf characteristics was carried out. It was discovered that form could be a key feature for identifying plants. This method holds much promise for assisting individuals in automatically identifying medicinal plants and conservation and utilization.

In the future, we intend to expand this research on the detection of thousands of medicinal plants by developing deep learning models and providing comprehensive software for this purpose.

REFERENCE

[1] Nawkar, M.G.; Maibam, P.; Park, J.H.; Sahi, V.P.; Lee, S.Y.; Kang, C.H. UV-induced cell death in plants. Int. J. Mol. Sci. 2013, 14, 1608–1628.

[2] Salehi, B.; Kumar, N.V.; ¸Sener, B.; Sharifi-Rad, M.; Kılıç, M.; Mahady, G.B.; Vlaisavljevic, S.; Iriti, M.; Kobarfard, F.; Setzer, W.N.; et al. Medicinal plants used in the treatment of human immunodeficiency virus. Int. J. Mol. Sci. 2018, 19, 1459.

[3] Pferschy-Wenzig, E.M.; Bauer, R. The relevance of pharmacognosy in pharmacological research on herbal medicinal products. Epilepsy Behav. 2015, 52, 344–362.

[4] Naeem, S., Ali, A., Chesneau, C., Tahir, M. H., Jamal, F., Sherwani, R. A. K., & Ul Hassan, M. (2021). The Classification of Medicinal Plant Leaves Based on Multispectral and Texture Feature Using Machine Learning Approach. Agronomy, 11(2), 263.

[5] Thella, P. K., & Ulagamuthalvi, V. A Comparative Analysis on Machine Learning Models for Accurate Identification of Medical Plants.

[6] Pushpanathan, K., Hanafi, M., Mashohor, S., & Fazlil Ilahi, W. F. (2021). Machine learning in medicinal plants recognition: a review. Artificial Intelligence Review, 54, 305-327.

[7] Herdiyeni, Y., Nurfadhilah, E., Zuhud, E. A., Damayanti, E. K., Arai, K., & Okumura, H. (2013). A computer-aided system for tropical leaf medicinal plant identification. International Journal on Advanced Science, Engineering and Information Technology, 3(1), 23-27.

[8] Putri, Y. A., Djamal, E. C., & Ilyas, R. (2021, March). Identification of Medicinal Plants Leaves Using Convolutional Neural Network. In Journal of Physics: Conference Series (Vol. 1845, No. 1, p. 012026). IOP Publishing.

[9] H. X. Kan, L. Jin, and F. L. Zhou," Classification of Medicinal Plant Leaf Image Based on Multi-Feature Extraction", Pattern Recognition and Image Analysis, Vol. 27, No. 3, 2017, pp. 581–587, 1054-6618. © Pleiades Publishing, Ltd.

[10] Riddhi H. Shaparia, Dr. Narendra M. Patel and Prof. Zankhana H. Shah," Flower Classification using Texture and Color Features", International Conference on Research and Innovations in Science, Engineering &Technology, Volume 2, 2017, Pages 113–118

[11] Pushpa BR, Anand C and MithunNambiar P," Ayurvedic Plant Species Recognition using Statistical Parameters on Leaf Images", International Journal of Applied Engineering Research, Volume 11, Number 7, 2016, 0973-4562.

[12] Sandeep Kumar E,"Leaf color, area and edge features based approach for identification of Indian medicinal plants", Indian Journal of Computer Science and Engineering (IJCSE), Vol. 3 No.3 Jun-Jul 2012, 0976-5166.

[13] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017, August). Understanding of a convolutional neural network. In 2017 International Conference on Engineering and Technology (ICET) (pp. 1-6). Ieee.

[14] Kim, P. (2017). Convolutional neural network. In MATLAB deep learning (pp. 121-147). Apress, Berkeley, CA.

[15] Li, Y., Hao, Z. B., & Lei, H. (2016). Survey of convolutional neural network. Journal of Computer Applications, 36(9), 2508-2515.

[16] Sarıgül, M., Ozyildirim, B. M., & Avci, M. (2019). Differential convolutional neural network. Neural Networks, 116, 279-287.

[17] O'Shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. arXiv preprint arXiv:1511.08458.

[18] Han, Z., Wei, B., Zheng, Y., Yin, Y., Li, K., & Li, S. (2017). Breast cancer multi-classification from histopathological images with structured deep learning model. Scientific reports, 7(1), 1-10.

[19] Abdollahi, J., Moghaddam, B. N., & Parvar, M. E. (2019). Improving diabetes diagnosis in smart health using genetic-based Ensemble learning algorithm. Approach to IoT Infrastructure. Future Gen Distrib Systems J, 1, 23-30.

[20] Abdollahi, J., Keshandehghan, A., Gardaneh, M., Panahi, Y., & Gardaneh, M. (2020). Accurate Detection of Breast Cancer Metastasis Using a Hybrid Model of Artificial Intelligence Algorithm. Archives of Breast Cancer, 18-24.

[21] Abdollahi, J., & Nouri-Moghaddam, B. (2022). Hybrid stacked ensemble combined with genetic algorithms for diabetes prediction. Iran Journal of Computer Science, 1-16.

[22] Abdollahi, J., Nouri-Moghaddam, B., & Ghazanfari, M. (2021). Deep Neural Network Based Ensemble learning Algorithms for the healthcare system (diagnosis of chronic diseases). arXiv preprint arXiv:2103.08182.

[23] Abdollahi, J., & Nouri-Moghaddam, B. (2021). Feature selection for medical diagnosis: Evaluation for using a hybrid Stacked-Genetic approach in the diagnosis of heart disease. arXiv preprint arXiv:2103.08175.

[24] Abdollahi, J. A review of Deep learning methods in the study, prediction and management of COVID-19.

[25] Raghukumar, A. M., & Narayanan, G. (2020, March). Comparison of machine learning algorithms for detection of medicinal plants. In 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC) (pp. 56-60). IEEE.

[26] Nagrath, P., Jain, R., Madan, A., Arora, R., Kataria, P., & Hemanth, J. (2021). SSDMNV2: A real time DNN-based face mask detection system using single shot multibox detector and MobileNetV2. Sustainable cities and society, 66, 102692.

[27] Abdollahi, J., & Mahmoudi, L. Investigation of artificial intelligence in stock market prediction studies.

[28] Abdollahi, J., Irani, A. J., & Nouri-Moghaddam, B. (2021). Modeling and forecasting Spread of COVID-19 epidemic in Iran until Sep 22, 2021, based on deep learning. arXiv preprint arXiv:2103.08178.

[29] abdollahi jafar, amani firouz, mohammadnia alireza, amani paniz, fattahzadeh-ardalani ghasem. Using Stacking methods based Genetic Algorithm to predict the time between symptom onset and hospital arrival in stroke patients and its related factors. JBE. 2022;8(1):8-23.