1.1 Introduction to Deep Learning

Artificial intelligence is the capability of a machine to imitate intelligent human behavior Machine learning (ML) is a branch of AI that gives computers the ability to “learn” often from data without being explicitly programmed. Deep learning is a subfield of ML that uses algorithms called artificial neural networks (ANNs), which are inspired by the structure and function of the brain and are capable of self-learning. ANNs are trained to “learn” models and patterns rather than being explicitly told how to solve a problem.

The building block of an ANN is called the perceptron, which is an algorithm inspired by the biological neuron *(5)*. Although the perceptron was invented in 1957, ANNs remained in obscurity until just recently because they require extensive training, and the amount of training to get useful results exceeded the computer power and data sizes available.

To appreciate the recent increase in computing power, consider that in 2012 the Google Brain project had to use a custom-made computer that consumed 600 kW of electricity and cost around $5,000,000. By 2014, Stanford AI Lab was getting more computing power by using three off-the-shelf graphics processing unit (GPU)-accelerated servers that each cost around $33,000 and consumed just 4 kW of electricity. Today, you can buy a specialized Neural Compute Stick that delivers more than 100 gigaflops of computing performance for $80.

Deep learning is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised. Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

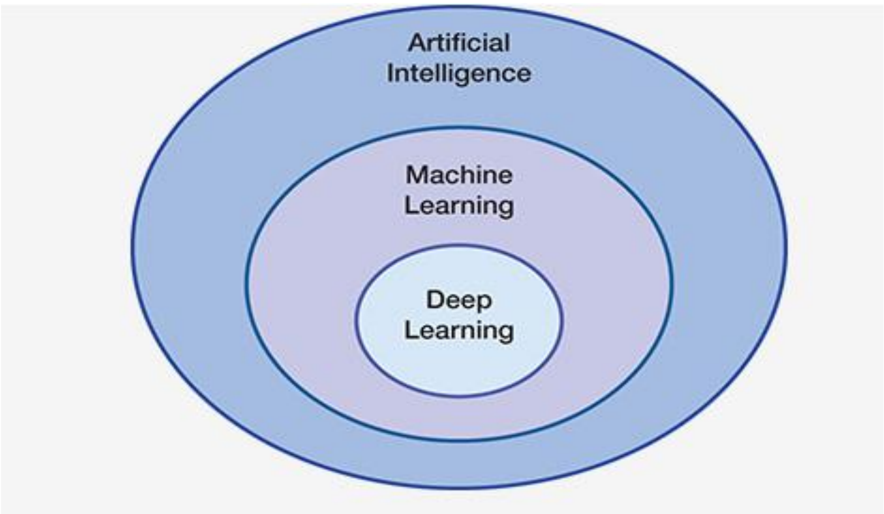


Figure 1.1.1 : Deep learning is a subfield of Machine Learning

Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, artificial neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analogue.

The adjective "deep" in deep learning refers to the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, but that a network with a nonpolynomial activation function with one hidden layer of unbounded width can. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

1.2 Introduction to Medicinal Plant Identification System

The world bears thousands of plant species, many of which have medicinal values, others are close to extinction, and still others that are harmful to man. Not only are plants an essential resource for human beings, but they form the base of all food chains. The medicinal plants are used mostly in herbal, ayurvedic and folk medicinal manufacturing.

Herbal plants are plants that can be used for alternatives to cure medicinals naturally. About 80% of people in the world still depend on traditional medicine. Meanwhile, according to herbal plants are plants whose plant parts (leaves, stems, or roots) have properties that can be used as raw materials in making modern medicines or traditional medicines. These medicinal plants are often found in the forest. There are various types of herbal plants that we can know through the identification of these herbs, one of which is using identification through the leaves. and protect plant species, it is crucial to study and classify plants correctly. Combinations of a small subset amounting to 1500 of these plants are used in Herbal medicines of different systems of India. Specifically, commercial Ayurvedic preparations use 500 of these plants. Over 80% of plants used in ayurvedic formulations are collected from the forests and wastelands whereas the remaining are cultivated in agricultural lands. More than 8000 plants of Indian origin have been found to be of medicinal value.

The general process of using traditional image recognition processing technology to identify medicinal plant is shown in Fig. 1.2.1.

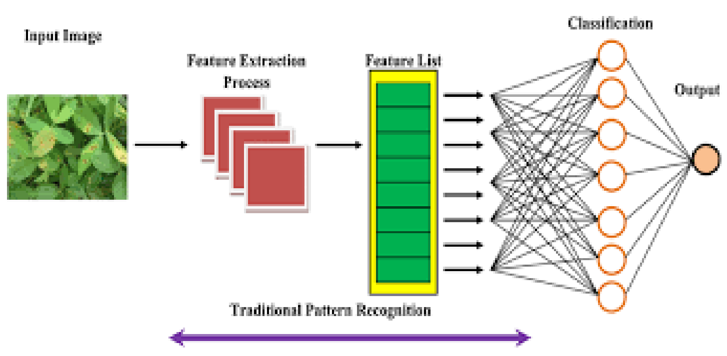


Fig 1.2.1: Traditional image recognition process.

2.1 Related Work

Jing et al. [1] In this research, CNN is applied to extract the features from leaf images of selected tree species. Three different CNN models were used, namely, the pre-trained AlexNet CNN model, fine-tuned pre-trained AlexNet CNN model and the proposed D-Leaf CNN model. The extracted features were then fed into a few classification approaches for learning and training purposes. Five classifiers were employed in this research which are CNN, Support Vector Machine (SVM), Artificial Neural Network (ANN), kNearest Neighbour (k-NN) and Naïve Bayes (NB).

Metre et al. [4] studied a conventional method, which segmented the leaf veins by using Sobel edge identification technique and performed vein morphological measurements, was used for benchmarking. Based on the literature review, this is one of the first few studies, which have applied CNN in tropical tree species classification, by using both leaf morphometric and venation pattern approaches.

Cope et al. [5] selected 5 kinds of medicinal plants species (Holy Basil plant, Indian warmwood , Indian Copperleaf, Asthama plant, and Indian Saraspilla) as the research objects. By extracting 8 features of the plants spot image, such as color, texture, and shape. The BP neural network model was used to classify and recognize the medicinal plants.

Anami et al. [6] There are endless plant species accessible all inclusive. To oversee gigantic substance, improvement of quick and successful classification techniques has transformed into a domain of dynamic exploration. As trees and plants are critical to environment, precise Identification and grouping gets important. Order strategy is helped out through number of sub techniques. A recognizable proof or Classification issue is overseen by planning an info information with one of the one of a kind classes. In this technique, from the start, database of a leaf pictures is made, that involves pictures of test leaf with their equal plant data. Fundamental highlights are removed utilizing picture preparing methods. The highlights must be steady so as to make the recognizable proof framework powerful. Consequently the plant/leaf is perceived utilizing AI procedures. In this paper a review is introduced on the different kinds of leaf distinguishing proof procedure.

Recently, the convolutional neural networks (CNN), a special of deep learning techniques, are quickly becoming the preferred methods [7]. CNN is the most popular classifier for image recognition, and it has shown outstanding ability in image processing and classification [8]. Deep learning approaches were first introduced in plant image recognition based on leaf vein patterns [9]. They used 3-6 layers CNN classified three leguminous plant species: white bean, red bean, and soybean.

Mohanty et al. [10] Plant species recognizable proof spotlights on the modified ID of plants. But a lot of points like leaf, owers, natural items, seeds could add to the decision, anyway leaf features are the most huge. As a plant leaf is for each situation continuously accessible when stood out from various bits of the plants, it is clear to peruse it for plant recognizable proof. The current paper introduced a novel plant creature bunches classifier considering the extraction of morphological features using a Multilayer Perceptron with Ad boosting. The proposed framework includes pre-getting ready, feature extraction, incorporate decision, and characterization. From the start, some pre-getting ready methodologies are used to set up a leaf picture for the segment extraction process. Distinctive morphological features, i.e., centroid, noteworthy turn length, minor center length, strength, outskirt, and heading are isolated from the propelled pictures of various orders of leaves. Unmistakable classifiers, i.e., k- NN, Decision Tree and Multilayer perceptron are used to test the precision of the count. Ada Boost approach is examined for improving the precision pace of the proposed structure. Test outcomes are procured on an open dataset (FLAVIA) downloaded from http://avia.sourceforge.net/. A precision pace of 95.42\% has been cultivated using the proposed AI classifier, which beat the state-of the craftsmanship counts.

Although particularly good results have been reported in the literature, however, the diversity of the used datasets is limited. Large datasets (comprised of thousands of images) are required for the training of CNNs. Unfortunately, for plant leaf recognition, such large and diverse datasets have not yet been collected for use by researchers. At present, transfer learning is the most effective way to train the robustness of CNN classifiers for medicinal plant recognition. Transfer learning enables the adaptation of pre-trained CNNs by retraining them with smaller datasets whose distribution is different from the larger datasets previously used to train the network from scratch [13]. Indeed, it is effective that using CNN models pre-trained on the ImageNet dataset and then retraining them for medicinal plant recognition.

Therefore, the combination of deep learning and transfer learning provides a new way to solve the problem of limited datasets of plant medicinals.

There are some research papers previously presented to summarize the research about agriculture (including plant medicinal recognition) by DL [8], [14], but they lacked some of the recent developments in terms of visualization techniques implemented along with the DL and modified the famous DL models, which were used for medicinal plant identification.

The article [15] presented many imaging techniques for plant medicinal identification, and the focus was on imaging techniques. The major techniques presented for medicinal plant identification and classification are SVM, K-means, and KNN.

The article [16] presented many developed/modified DL architectures implemented to detect and classify plant medicinals. And provided a comprehensive explanation of DL models used to visualize various medicinal plant identification.

In the paper [17], the authors had presented a comprehensive review of recent research work done in medicinal plant recognition using IPTs, from the perspective of feature extracted based on hand-crafted or using deep learning techniques. And it is concluded that the deep learning. techniques have superseded shallow classifiers trained using hand-crafted features. But they lacked some of the recent developments in terms of visualization techniques, and there is no mention of the identification of the medicinal plants and how to detect and classify medicinal plant based on small samples.

Tian et al. [21] An arrangement approach based on Random Forests (RF) and Linear Discriminant Analysis (LDA) calculations for arranging the various kinds of plants. The proposed approach comprises of three stages that are pre-preparing, include extraction, and order stages. Since most kinds of plants have novel leaves, so the order approach introduced in this examination relies upon plants leave. Leaves are not the same as each other by qualities, for example, the shape, shading, surface and the edge. The utilized dataset for this investigations is a database of various plant species with all out of just 340 leaf pictures, was downloaded from UCI-Machine Learning Repository. It was utilized for both preparing and testing datasets with lO-crease cross-approval. Exploratory outcomes indicated that LDA accomplished order precision of (92.65 \%) against the RF that accomplished precision of (88.82 \%) with mix of shape, first request surface, Gray Level Co

In the paper [24], five different kinds of holy basil leaf images were expanded by a novel Leaf GAN model. The experimental results showed that the Leaf GAN model could make the holy basil leaf images highlight the medicinal uses and generate enough holy basil plant images. It was proved that Leaf GAN was superior to those of the DCGAN and WGAN.

Cope et al. [5]_Plant species identification focuses on the programmed identification of plants. Albeit a great deal of angles like leaf, owers, organic products, seeds could add to the choice, however leaf highlights are the most significant. As a plant leaf is in every case progressively available when contrasted with different pieces of the plants, it is clear to read it for plant identification. The current paper presented a novel plant animal groups classifier in light of the extraction of morphological highlights utilizing a Multilayer Perceptron with Adaboosting. The proposed system involves prepreparing, highlight extraction, include choice, and classification. At first, some pre-preparing strategies are utilized to set up a leaf picture for the component extraction process. Different morphological highlights, i.e., centroid, significant pivot length, minor hub length, robustness, border, and direction are separated from the advanced pictures of different classifications of leaves. Distinctive classiers, i.e., k-NN, Decision Tree and Multilayer perceptron are utilized to test the exactness of the Sigit Adinugroho, Yuita Arum Sari visual results clearly showed the medicinal plants spots also.

In Cruz et al. [27],the improved LeNet model was used to detect olive plant medicinals, that is, segmentation and edge maps were used to identify plant medicinals. Brahimi et al. [28] proposed a new visualization method, that is, a new DL model teacher/student network was introduced to identify the spots of plant medicinals, compared with the existing plant medicinal treatment methods, the new method obtained a clearer visualization effect.

According to the author Dechant et al. [29], using different CNN combinations, the visual heat map of plant images was used as the inputs, and the probability associated with the occurrence of a particular type of medicinal plants and their uses was given. The ROC curve was used to evaluate the performance of the model. In addition, the characteristic map plant identifications was also drawn.

Lu et al. [30] realized that Indian saraspilla plant identification by using VGG-FCN and VGG-CNN model and visualized the module features. The results showed that the DMIL-WDDS based on VGGFCN-VD16 achieved a progressive learning process for fine characteristics of the medicinal. The feature visualization was a good demonstration of what the DMIL-WDDS was learning. Moreover, the results indicated that Softmax aggregation was a superior choice for DMIL-WDDS to improve the recognition accuracy.

Ha et al. [31] used the VGG-CNN model to test the blight of radish and used the k-means clustering method to show the medicinal plants markers. And the method was able to identify the individual plants. That is, the regions of medicinal uses and moderate Fusarium wilt of plants were successfully identified by the method. The results showed that the method can also be applied to other crops and plants, including asthama plant, holy basil, Indian warmwood, and etc.

Barbedo [32] explored the use of individual lesions and uses for the task, rather than considering the entire plants, and by using the DL models to identify the medicinal plant. The accuracy obtained using the approach was, on average, 12% higher than those achieved using the original images.

Ghosal et al. [33], developed a deep CNN framework to identify and classify 8 kinds of plant stress. And also present an explanation mechanism, used the top-K high resolution feature maps that isolate the visual symptoms to make predictions. The unsupervised identification of visual symptoms provided a quantitative measure of stress severity, allowing for identification (a type of foliar stress), classification (low, medium, or high stress), without detailed symptom annotation by experts.

Lu et al. [34] Use of the benefits of present day enlisting advancement to improve the capability of plant fields is inevitable with creating stresses over extending world masses and limited food resources.

Preparing advancement is imperative not solely to endeavors related to food creation yet moreover to hearty individuals and other related authorities. It isn't unexpected to extend the gainfulness, add to an unrivaled appreciation of the association between common segments and strong harvests, reduce the work costs for farmers and addition the movement speed and accuracy.

Picon et al. [35] proposed an adapted algorithm based on a deep residual neural network to deal with the identification of multiple medicinal plants in real conditions for early medicinal plant identification. And developed a mobile application in which heat maps were used to identify medicinal plant . Obtained results reveal an overall improvement of the balanced accuracy up to 0.87 under exhaustive testing, and the accuracy greater than 0.96 on a pilot test performed in Germany.

Johannes et al. [36] used an algorithm based on heat map technology to extract the medicinal objects. In addition, each heat map is described by two descriptors, one for evaluating the color information of the medicines, and the other for identifying the texture of the heat map. The preliminary hot-spot identification and its ulterior description by color and textural descriptors allow real-time performance as only the suspicious regions are trained and described by the higher-level classifiers and descriptors.

Khan et al. [37] proposed a new visualization technology using correlation coefficient and DL model (e.g., AlexNet and VGG16 architecture). Kerkech et al. [38] variety vegetation indices in color space combined with the LeNet model were used to detect the medicinal plants.

The article [39] for the reason of interpreting the deep learning model, compared with some of the most popular explanatory methods: significant figure, Smooth-Grad, boot back-propagation, depth Taylor decomposition, integration gradient layered associated transmission, and gradient time input. And trained the DenseNet121 network to identify eight different basil stresses (biological and non-biological). And concluded that the interpretability methods identified the features regions of the plants as notable features for some (but not all) of the correctly classified images. Taken Asthama plant images (asthama plant of 261 images of 5 kinds of common medicinal plants) in the complex background as the research object.

Sun et al. [40] proposed a method combining simple linear iterative clustering (SLIC) and support vector machine (SVM) and gain a significant figure accurate asthama a medicinal plant image, with 73.5% accuracy, precision is 96.8%, the recall rate was 98.6%, the F1 score was 97.7%. The results showed that the method can effectively extract asthama plants from complex background significant figure.

Hu et al. [41] put forward a kind of new convolution neural network model ARNet (Attention residual network) combining the attention mechanism with the residual idea, in the early and late periods were studied. The results of the study concluded that, compared with the existed models such as VGG16, the ARNet had a better classification performance.

Since each medicinal plants has its own characteristics, Barbedo [32] and Lee et al. [42], discussed the use of individual lesions and uses rather than considering the whole plant. The advantages of this method were that occurrence of multiple medicinal uses on the same plant could be detected and the data can be augmented by cutting up the plant image into multiple sub-images.

The article [45] taken 79 medicinals of 14 species of plants in the experimental environment and complex field environment as the research object and used the GoogLeNet model to identify medicinal plants. The overall accuracy of using a single lesion and uses was 94%, which was higher than using the whole image (82%).

Lee et al. [42] put forward a new view of medicinal plant identification that focused on identifying the plant and their medicinal uses area method (i.e., by the common name of plants rather than seeds - identifications on the target category), and through the experiments showed that whatever plant species, the model training with the common medicinal use were more universal, especially for the new data obtained in different fields or that plant species have not been seen.

Qiu et al. [43] used the Mask-RCNN whose feature extraction network was ResNet50 or ResNet101 to detect the wheat medicinal areas, Ahmad et al. [44] used four different pretraining convolution neural networks VGG19, VGG16, ResNet, and Inception V3, and the models were trained by fine-tuning parameters. The experimental results showed that the Inception V3 had the best performance on the two datasets (the laboratory dataset and the field dataset). And the average performance superior to 10% to 15% on the laboratory dataset compared with on the field dataset.

Bi et al. [45] showed that the recognition accuracy rates of Holy basil plant and rust models collected by agricultural experts were 77.65%, 75.59%, and 73.50%, by using ResNet152, Inception V3, and MobileNet, respectively.

Jiang et al. [46] used the Mean Shift algorithm to segment five kinds of plants And their medicinal uses first, and then extract shape feature by artificial calculation (put forward three new shape characteristic lesions number N, S lesion area, number of lesions ratio R) and CNN extracts color feature, at last, the SVM classifier was used to identify the plants (medicinal), and the results showed that the CNN used segmentation algorithm accuracy was 92.75%, the accuracy was 82.26% without the segmentation algorithm, and the accuracy of the CNN in combination with the SVM model was 96.8%.

Liang et al. [47] established a dataset contains 2906 of the positive samples and 2902 of the negative samples to identify blasts. And the experimental results showed that the senior characteristics extracted from CNN than the traditional manual extraction of local binary pattern histogram (LBPH) and wavelet transform (Haar-WT) had better identification and effectiveness.

Huang et al. [48] put forward a kind of medicinal plant recognition method based on the neural structure search algorithm, the method can learn the structure of the neural network to the appropriate depth on the PantVillage, automatically. According to the results of the studied methods on the dataset of imbalanced and balanced searched out a suitable network structure, and the recognition accuracy of the model was 98.96% and 99.01% respectively. However, if the balance of the gray images was not improved, the accuracy fell to 95.40%.

Long et al. [49] used AlexNet for 2 kinds of training, that is, training from scratch and transfer learning from the ImageNet to detect the camellia leaf medicinals (4 kinds of medicinals and healthy). The results showed that transfer learning can significantly improve the convergence speed and classification performance of the models, and the classification accuracy as high as 96.53%.

Xu et al. [50] Plant species identification focuses on the programmed identification of plants. Albeit a great deal of angles like leaf, owers, organic products, seeds could add to the choice, however leaf highlights are the most significant. As a plant leaf is in every case progressively available when contrasted with different pieces of the plants, it is clear to read it for plant identification.

The current paper presented a novel plant animal groups classifier in light of the extraction of morphological highlights utilizing a Multilayer Perceptron with Ad boosting.

The proposed system involves preparing, highlight extraction, include choice, and classification. At first, some pre-preparing strategies are utilized to set up a leaf picture for the component extraction process. Different morphological highlights, i.e., centroid, significant pivot length, minor hub length, robustness, border, and direction are separated from the advanced pictures of different classifications of leaves.

Distinctive classier, i.e., k-NN, Decision Tree and Multilayer perceptron are utilized to test the exactness of the calculation. AdaBoost approach is investigated for improving the exactness pace of the proposed framework. Test results are acquired on an open dataset (FLAVIA) downloaded from http://avia.sourceforge.net/. An accuracy pace of 95.42\% has been accomplished utilizing the proposed AI classifier, which beat the state of the craftsmanship calculations.

2.2 Summary and Discussion

This dissertation implements Medicinal Plant Identification system using deep learning. Deep learning techniques are capable of recognizing plant Species with high accuracy. The importance of collecting large datasets with high variability, data augmentation, transfer learning, and visualization of CNN activation maps in improving classification accuracy, and the importance of small sample plant Species Identification and the importance of hyper-spectral imaging for Plant Species Identification have been discussed.

3.1 Motivation

In the ancient past, the Ayurvedic physicians themselves picked the medicinal plants and prepared the medicines for their patients. Today only a few practitioners follow this practice. The commercialization of Ayurvedic sector has brought in to focus several questions regarding the quality of raw materials used for Ayurvedic medicines. Today the plants are collected by women and children from forest areas; those are not professionally trained in identifying correct medicinal plants. Manufacturing units often receive incorrect or substituted medicinal plants. The recognition of plant leaves is a vital process. in botany and in tea, cotton and other industries and is also used during early diagnosis of plant detects like medicinals. Thus, automatic plant classification is vital to these endeavours and is considered by this research work.

3.2 Objectives

- To collect the data from dataset of medicinal plants.
- To prepare the suitable data from raw data of the specific plant.
- To extract the features from raw data of medicinal plant using CNN algorithm
- To train the model for prediction of medicinal plant and display the use of that specific plant.
- To measure the performance of system and the accuracy of the prediction of medicinal plant.

4.1 Problem Definition

Medicinal plants have provided mankind a large variety of potent drugs to alleviate or eradicate infections and suffering from medicinals in spite of advancement in synthetic drugs, some of the plant-derived drugs still retained their importance and relevance. The use of plant-based drugs all over world is increasing. There have been records of advances made in the modern (synthetic) medicine there are still a large number of ailments or infection (medicinals) for which suitable drugs are yet to be found. This have brought an urgent need to develop safer drugs (both for man and his environment) for the treatment of inflammatory disorders, diabetes, liver medicinals, and gastrointestinal disorder. Through recent researches on herbal plants or medicine, there have been great developments in the pharmacological evaluation of various plants used in traditional systems of medicine. Consequently, plants can be described as a major source of medicines, not only as isolated active principles to be dispensed in standardized dosage form but also as crude drugs for the population. Modern medicines and herbal medicines are complimentarily being used in areas for health care program in several developing countries such as countries in Africa, Asia and some part of Europe. Due to different outcomes on herbal plants, plant products surfaces all over the world due to the belief that many herbal medicines are known to be free from health and environmental effects. The fear of the masses in the utility of synthetic drug or modern drugs is always accompanied with its single or multiple adverse or health effects.

4.2 System Design

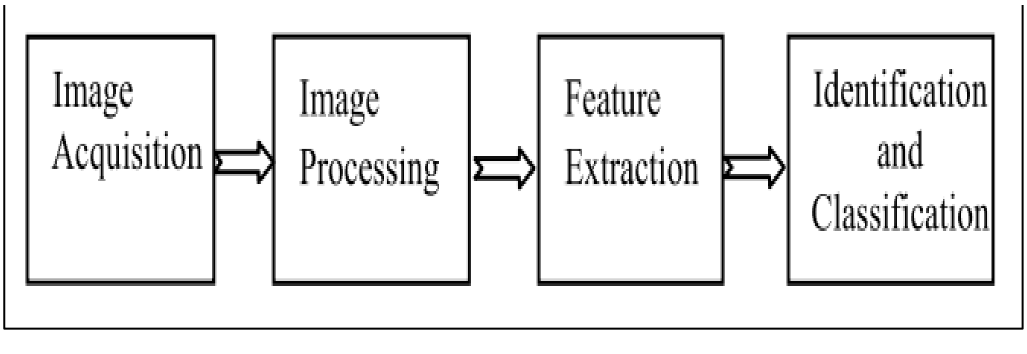


Figure 4.2.1: Flow of Image Identification.

The general process of using traditional image recognition processing technology to identify plant medicinals is shown in Fig. 4.2.1.

Image Acquisition: Image Acquisition is the first step in any image processing system. The general aim of any image acquisition is to transform an optical image (real-world data) into an array of numerical data which could be later manipulated on a computer. Image acquisition is achieved by suitable cameras. We use different cameras for different applications. If we need an X-ray image, we use a camera (film) that is sensitive to X-rays. If we want an infrared image, we use cameras that are sensitive to infrared radiation. For normal images (family pictures, etc.), we use cameras that are sensitive to the visual spectrum.

Image Processing: An image is represented by its dimensions (height and width) based on the number of pixels. For example, if the dimensions of an image are 500 x 400 (width x height), the total number of pixels in the image is 200000. This pixel is a point on the image that takes on a specific shade, opacity or color. It is usually represented in one of the following:

- Grayscale - A pixel is an integer with a value between 0 to 255 (0 is completely black and 255 is completely white).
- RGB - A pixel is made up of 3 integers between 0 to 255 (the integers represent the intensity of red, green, and blue).
- RGBA - It is an extension of RGB with an added alpha field, which represents the opacity of the image.

Image processing requires fixed sequences of operations that are performed at each pixel of an image. The image processor performs the first sequence of operations on the image, pixel by pixel. Once this is fully done, it will begin to perform the second operation, and so on. The output value of these operations can be computed at any pixel of the image.

Image processing is the process of transforming an image into a digital form and performing certain operations to get some useful information from it. The image processing system usually treats all images as 2D signals when applying certain predetermined signal processing system.

There are five main types of image processing:

- Visualization - Find objects that are not visible in the image
- Recognition - Distinguish or detect objects in the image
- Sharpening and restoration - Create an enhanced image from the original image
- Pattern recognition - Measure the various patterns around the objects in the image
- Retrieval - Browse and search images from a large database of digital images that are similar to the original image

Feature Extraction: Feature extraction is a part of the dimensionality reduction process, in which, an initial set of the raw data is divided and reduced to more manageable groups. So when you want to process it will be easier. The most important characteristic of these large data sets is that they have a large number of variables. These variables require a lot of computing resources to process. So Feature extraction helps to get the best feature from those big data sets by selecting and combining variables into features, thus, effectively reducing the amount of data. These features are easy to process, but still able to describe the actual data set with accuracy and originality. The technique of extracting the features is useful when you have a large data set and need to reduce the number of resources without losing any important or relevant information. Feature extraction helps to reduce the amount of redundant data from the data set. In the end, the reduction of the data helps to build the model with less machine effort and also increases the speed of learning and generalization steps in the machine learning process.

Identification and Classification: In simple words, image classification is a technique that is used to classify or predict the class of a specific object in an image. The main goal of this technique is to accurately identify the features in an image. In general, the image classification techniques can be categorized as parametric and non-parametric or supervised and unsupervised as well as hard and soft classifiers. For supervised classification, this technique delivers results based on the decision boundary created, which mostly rely on the input and output provided while training the model. But, in the case of unsupervised classification, the technique provides the result based on the analysis of the input dataset own its own; features are not directly fed to the models. The main steps involved in image classification techniques are determining a suitable classification system, feature extraction, selecting good training samples, image pre-processing and selection of appropriate classification method, post-classification processing, and finally assessing the overall accuracy. In this technique, the inputs are usually an image of a specific object, such as the rabbit in the above picture, and the outputs are the predicted classes that define and match the input objects. Convolutional Neural Networks (CNNs) is the most popular neural network model that is used for image classification problem.

4.3 Feasibility study

Feasibility Study in Software Engineering is a study to evaluate feasibility of proposed project or system. Feasibility study is one of stage among important four stages of Software Project Management Process. As name suggests feasibility study is the feasibility analysis or it is a measure of the software product in terms of how much beneficial product development will be for the organization in a practical point of view. Feasibility study is carried out based on many purposes to analyze whether software product will be right in terms of development, implantation, contribution of project to the organization etc.

Types of Feasibility Study:

The feasibility study mainly concentrates on below five mentioned areas. Among these Economic Feasibility Study is most important part of the feasibility analysis and Legal Feasibility Study is less considered feasibility analysis.

- **Technical Feasibility –** In Technical Feasibility current resources both hardware software along with required technology are analyzed/assessed to develop project. This technical feasibility study gives report whether there exists correct required resources and technologies which will be used for project development. Along with this, feasibility study also analyzes technical skills and capabilities of technical team, existing technology can be used or not, maintenance and up-gradation is easy or not for chosen technology etc.
- **Operational Feasibility –** In Operational Feasibility degree of providing service to requirements is analyzed along with how much easy product will

be to operate and maintenance after deployment. Along with these other operational scopes are determining usability of product, determining suggested solution by software development team is acceptable or not etc.

- **Economic Feasibility –** In Economic Feasibility study cost and benefit of the project is analyzed. Means under this feasibility study a detail analysis is carried out what will be cost of the project for development which includes all required cost for final development like hardware and software resource required, design and development cost and operational cost and so on. After that it is analyzed whether project will be beneficial in terms of finance for organization or not.
- **Legal Feasibility –** In Legal Feasibility study project is analyzed in legality point of view. This includes analyzing barriers of legal implementation of project, data protection acts or social media laws, project certificate, license, copyright etc. Overall, it can be said that Legal Feasibility Study is study to know if proposed project conforms legal and ethical requirements.
- **Schedule Feasibility –** In Schedule Feasibility Study mainly timelines/deadlines are analyzed for proposed project which includes how many times teams will take to complete final project which has a great impact on the organization as purpose of project may fail if it can’t be completed on time.

4.4 Requirement Analysis

Minimum Hardware Requirement

- System Core i3 1.80 GHz Processor

A processor is the logic circuitry that responds to and processes the basic instructions that drive a computer.

- Hard Disk: 100 GB or higher.

The main function of hard disk is to store data for long term and data can be computer's operating systems, applications, documents, personal files and so on.

- Ram: 4 GB or higher.

Computer random access memory (RAM) is one of the most important components in determining your system's performance. RAM gives applications a place to store and access data on a short-term basis. It stores the information your computer is actively using so that it can be accessed quickly.

Minimum Software Requirement

- Operating System: Windows 11

  An operating system (OS) is system software that manages computer hardware, software resources, and provides common services for computer programs.

- Technology Used: PHP

  PHP is a general-purpose scripting language especially suited to web development.

- Database Used: MySQL

  MySQL Database Service is a fully managed database service to deploy cloud-native applications.

- Library: jQuery

  Query is a JavaScript library designed to simplify HTML DOM tree traversal and manipulation, as well as event handling, CSS animation, and Ajax.

4.5 System Configuration

- **Install XAMPP.**

Steps:

1. **Download:** XAMPP is a release made available by the non-profit project Apache Friends. Versions with PHP 5.6, or 7.4 are available for download on the Apache Friends website.
2. **Run .exe file:** Once the software bundle has been downloaded, you can start the installation by double clicking on the file with the ending .exe.
3. **Deactivate any Antivirus Software:** Since an active antivirus program can negatively affect the installation process, it's recommended to temporarily pause any antivirus software until all XAMPP components have successfully been installed.

4.**Deactivate UAC:** User Account Control (UAC) can interfere with the XAMPP installation because it limits writing access to the C: drive, so we recommend you deactivate this too for the duration of the installation process. To find out how to turn off your UAC, head to the Microsoft Windows support pages.

5.**Start The Setup Wizard:** After you've opened the .exe file (after deactivating your antivirus program(s) and taken note of the User Account Control, the start screen of the XAMPP setup wizard should appear automatically. Click on 'Next' to configure the installation settings.

6.**Choose Software Components:** Under 'Select Components', you have the option to exclude individual components of the XAMPP software bundle from the installation. But for a full local test server, we recommend you install using the standard setup and all available components. After making your choice, click 'Next'.

7.**Choose The Installation Directory:** In this next step, you have the chance to choose where you'd like the XAMPP software packet to be installed. If you opt for the standard setup, then a folder with the name XAMPP will be created under C:\ for you. After you've chosen a location, click 'Next'.

8.**Start The Installation Process:** Once all the aforementioned preferences have been decided, click to start the installation. The setup wizard will unpack and install the selected components and save them to the designated directory. This process can take several minutes in total. You can follow the progress of this installation by keeping an eye on the green loading bar in the middle of the screen.

9.**Windows Firewall Blocking:** Your Firewall may interrupt the installation process to block some components of the XAMPP. Use the corresponding check box to enable communication between the Apache server and your private network or work network. Remember that making your XAMPP server available for public networks isn't recommended.

10. **Complete Installation:** Once all the components are unpacked and installed, you can close the setup wizard by clicking on 'Finish'. Click to tick the corresponding check box and open the XAMPP Control Panel once the installation process is finished.

- **Import dump sql file into php my admin**

1. Log into phpMyAdmin.
2. Select the destination database on the left pane.
3. Click on the Import tab in the top center pane.
4. Under the File to import section, click Browse and locate the file with the .
5. Check or uncheck the boxes for 'Partial import' and 'Other options'.
6. From the Format dropdown menu choose 'SQL'.
7. Click the **Go** button at the bottom to import the database.

- **Create your project folder in XAMPP.>> Htdocs>> and copy all the files in it.**

Find an open space in the right pane and right click or on newer versions of Windows, Click the drop-down arrow beside Organize top left, and choose New Folder. Either method, Type htdocs to replace the blue New Folder text. Then click beside it. Then double click the htdocs folder to open it.

- **Start apache server and execute the project on local host.**
  1. In order to get the dashboard for localhost: search http://localhost in any browser.
  2. Now to run your code, open localhost/file.php then it gets executed.

4.6 Setting Environment

Client side and server-side environment

Client side and server side are web development terms that describe where application code runs. Web developers will also refer to this distinction as the frontend vs. the backend, although client-side/server-side and frontend/backend aren't quite the same. In a serverless architecture, the serverless vendor hosts and assigns resources to all server-side processes, and the processes scale up as application usage increases.

Client-server model

Much of the Internet is based on the client-server model. In this model, user devices communicate via a network with centrally located servers to get the data they need, instead of communicating with each other. End user devices such as laptops, smartphones, and desktop computers are considered to be 'clients' of the servers, as if they were customers obtaining services from a company. Client devices send requests to the servers for webpages or applications, and the servers serve up responses.

The client-server model is used because servers are typically more powerful and more reliable than user devices. They also are constantly maintained and kept in controlled environments to make sure they're always on and available; although individual servers may go down, there are usually other servers backing them up. Meanwhile, users can turn their devices on and off, or lose or break their devices, and it should not impact Internet service for other users.

Servers can serve multiple client devices at once, and each client device sends requests to multiple servers in the course of accessing and browsing the Internet.

Multiple clients and servers interact:Suppose a user is browsing the Internet and types 'netflix.com' into their browser bar. This results in a request to DNS servers for the IP address of netflix.com, and the DNS servers respond to this request by serving the IP address to the browser. Next, the user's browser makes a request to Netflix servers (using the IP address) for the content that appears on the page, such as the movie thumbnail images, the Netflix logo, and the search bar. Netflix servers deliver this to the browser, and the browser loads the page on the client device.

Client side of Application

In web development, 'client side' refers to everything in a web application that is displayed or takes place on the client (end user device). This includes what the user sees, such as text, images, and the rest of the UI, along with any actions that an application performs within the user's browser.

Markup languages like HTML and CSS are interpreted by the browser on the client side. In addition, many contemporary developers are including client-side processes in their application architecture and moving away from doing everything on the server side; business logic for dynamic webpages*, for instance, usually runs client side in a modern web application. Client-side processes are almost always written in JavaScript.

In the netflix.com example above, the HTML, CSS, and JavaScript that dictate how the Netflix main page appears to the user are interpreted by the browser on the client side. The page can also respond to 'events': For instance, if the user's mouse hovers over one of the movie thumbnail images, the image expands and adjacent thumbnails move slightly to one side to make room for the larger image. This is an example of a client-side process; the code within the webpage itself responds to the user's mouse and initiates this action without communicating with the server.

The client side is also known as the frontend, although these two terms do not mean precisely the same thing. Client-side refers solely to the location where processes run, while frontend refers to the kinds of processes that run client-side.
A dynamic webpage is a webpage that does not display the same content for all users and changes based on user input. The Facebook homepage is a dynamic page; the Facebook login page is for the most part static.

Server side of Application

Much like with client side, 'server side' means everything that happens on the server, instead of on the client. In the past, nearly all business logic ran on the server side, and this included rendering dynamic webpages, interacting with databases, identity authentication, and push notifications.

The problem with hosting all of these processes on the server side is that each request involving one of them has to travel all the way from the client to the server, every time. This introduces a great deal of latency. For this reason, contemporary applications run more code on the client side; one use case is rendering dynamic webpages in real time by running scripts within the browser that make changes to the content a user sees.

Like with 'frontend' and 'client-side,' backend is also a term for the processes that take place on the server, although backend only refers to the types of processes and server-side refers to the location where processes run.

5.1 Proposed Algorithm

CNN Algorithm

Convolutional Neural Network is one of the techniques to do image classification and image recognition in neural networks. It is designed to process the data by multiple layers of arrays. This type of neural network is used in applications like image recognition or face recognition. The primary difference between CNN and other neural network is that CNN takes input as a two-dimensional array. And it operates directly on the images rather than focusing on feature extraction which other neural networks do.

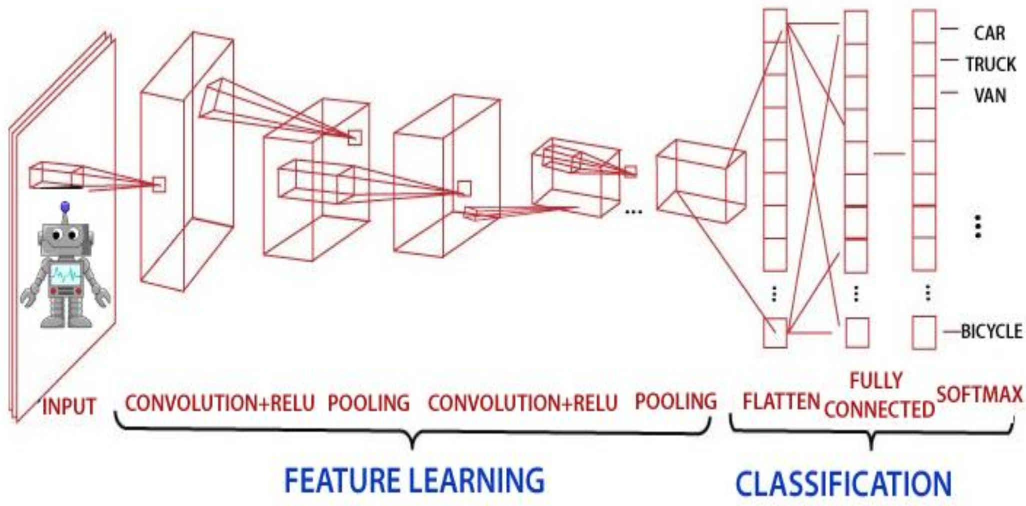


Figure 5.1.1: CNN Layers

The dominant approach of CNN includes the solution for problems of recognition. Some companies like Google and Facebook have invested in the field research and development concerning recognition projects to get activities done with higher speed. Scene labeling, object identification, and face recognition, etc. are some of the areas where Convolutional Neural Network works. Convolutional Neural Network (CNN or ConvNet) is a type of feed-forward artificial network where the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex.

Origin of Convolutional Neural Networks

The intelligence of neural networks is unnatural. While the artificial neural network is researched as early in the 1960s by Rosenblatt, it was only in late 2000s when deep learning using neural networks took off. The key enabler was the scale of computation power and datasets with Google developing research into deep learning. In July 2012, researchers at Google disclosed an advanced neural network to a series of unlabeled, static images sliced from YouTube videos.

For example, consider this image of Nature, upon first glance; we will see a lot of buildings and colors.

How Does a computer read an image?

The image is broken into 3 color-channels which is Red, Green, and Blue. Each of these color channels is mapped to the image's pixel.

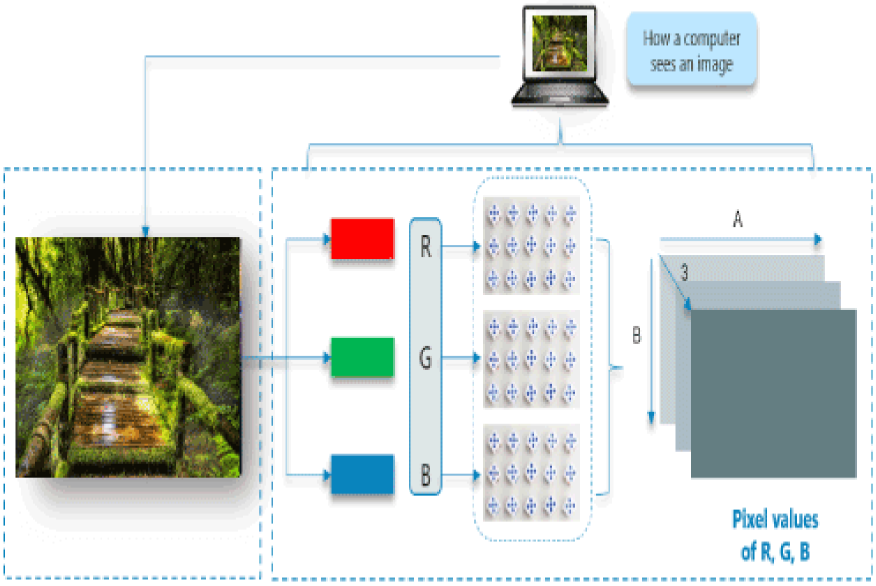


Figure 5.1.2: Image Reading

Some neurons fires when exposed to vertices edges and some when shown horizontal or diagonal edges. CNN utilizes spatial correlations which exist with the input data. Each concurrent layer of the neural network connects some input neurons. This region is called a local receptive field. The local receptive field focuses on hidden neurons.The hidden neuron processes the input data inside the mentioned field, not realizing the changes outside the specific boundary.

Convolutional Neural Networks have the following 4 layers:

1. Convolutional
2. ReLU Layer
3. Pooling
4. Fully Connected

1. Convolutional layer: Convolution layer is the first layer to derive features from the input image. The convolutional layer conserves the relationship between pixels by learning image features using a small square of input data. It is the mathematical operation which takes two inputs such as image matrix and kernel or any filter.

i. The dimension of image matrix is h×w×d.
ii. The dimension of any filter is fh×fw×d.
iii. The dimension of output is (h-fh+1)×(w-fw+1)×1.

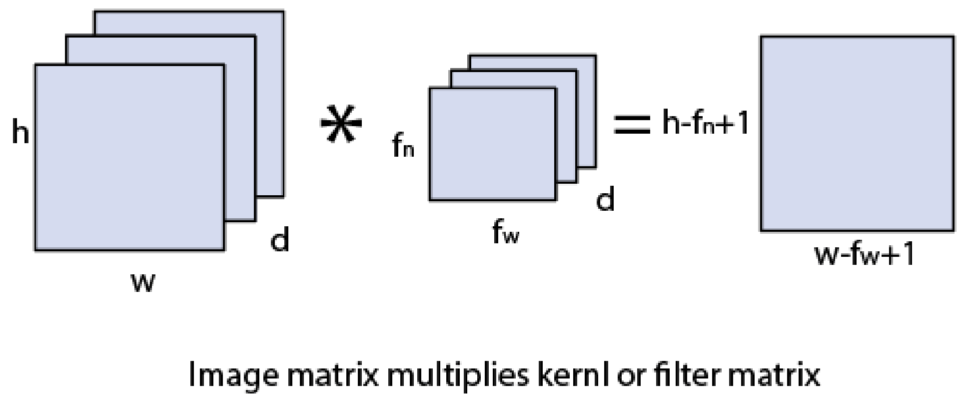


Figure 5.1.3: Image Matrix

2. ReLU Layer: Rectified Linear unit (ReLU) transform functions only activates a node if the input is above a certain quantity. While the data is below zero, the output is zero, but when the input rises above a certain threshold. It has a linear relationship with the dependent variable. In this layer, we remove every negative value from the filtered images and replaces them with zeros. It is happening to avoid the values from adding up to zero.

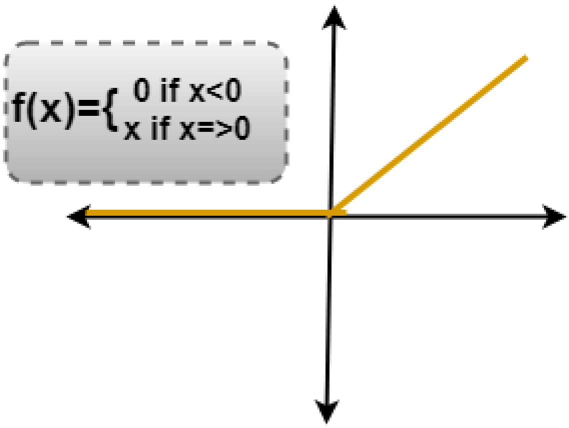


Figure 5.1.4: Graphical Representation of f(x)

3. **Pooling Layer:** Pooling layer plays a vital role in pre-processing of any image. Pooling layer reduces the number of the parameter when the image is too large. Pooling is "downscaling" of the image achieved from previous layers. It can be compared to shrink an image to reduce the image's density. Spatial pooling is also called downsampling and subsampling, which reduce the dimensionality of each map but remains essential information. These are the following types of spatial pooling.

   We do this by implementing the following 4 steps:

- Pick a window size (usually 2 or 3)
- Pick a stride (usually 2)
- Walk your window across your filtered images
- From each window, take the maximum value

   i. **Max Pooling:** Max pooling is a sample-based discretization process. The main objective of max-pooling is to downscale an input representation, reducing its dimension and allowing for the assumption to be made about feature contained in the sub-region binned. Max pooling is complete by applying a max filter in non-overlapping sub-regions of initial representation.

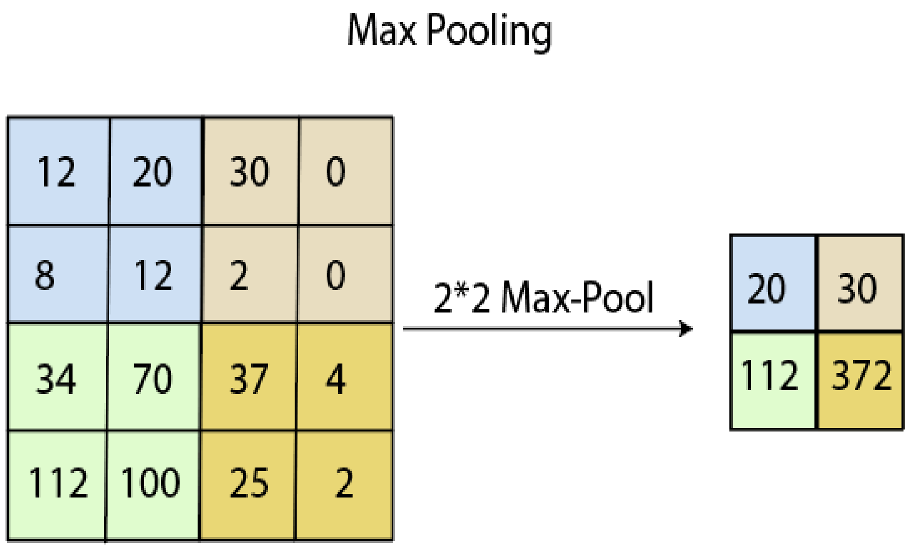


Figure 5.1.5: Max Pooling 2*2

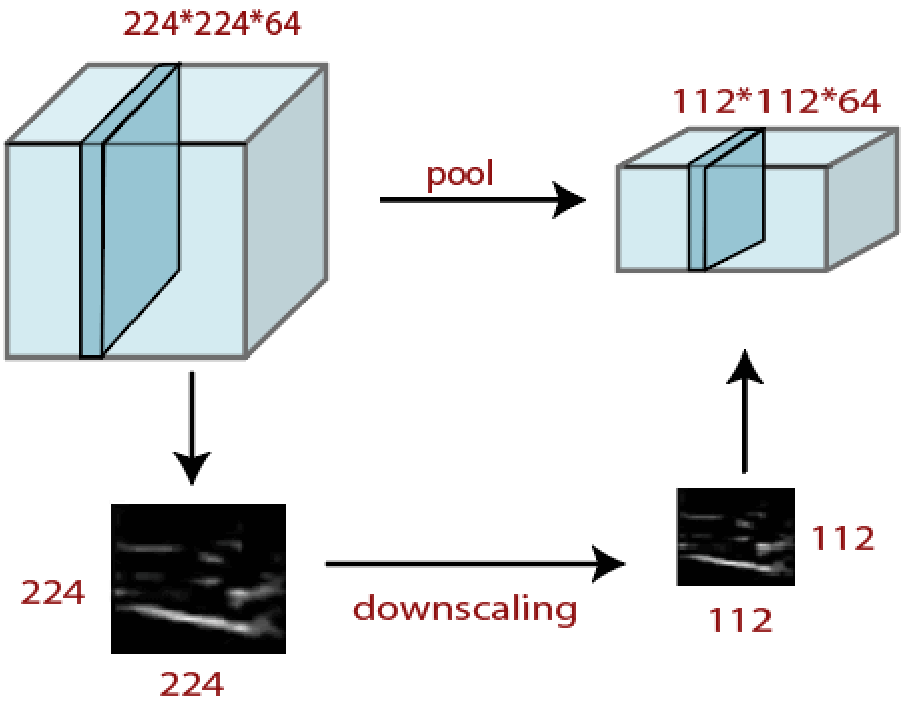


Figure 5.1.6: Max Pooling

ii. **Average Pooling:** Down-scaling will perform by average pooling by dividing the input into rectangular pooling regions and computing the average values of each area.

iii. **Sum Pooling:** The sub-region for sum pooling and mean pooling are set the same as for max-pooling but instead of using the max function.

In this layer we shrink the image stack into a smaller size steps:

1. Pick a window size (usually 2 or 3)
2. Pick a stride (usually 2)
3. Walk our window across our filtered images.
4. From each window, take the maximum value.
5. Performing pooling with a window size two and stride 2.

4. **Fully Connected (Dense) Layer:** The fully connected layer (dense layer) is a layer where the input from other layers will be depressed into the vector. It will transform the output into any desired number of classes into the network.

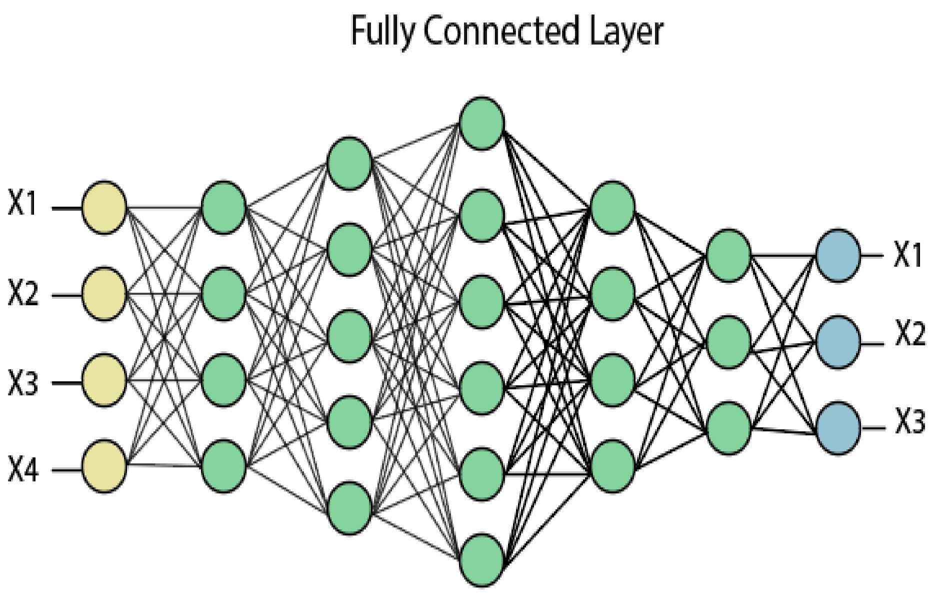


Figure 5.1.7: Fully Connected Layer

In the above diagram, the map matrix is converted into the vector such as x1, x2, x3... xn with the help of a fully connected layer. We will combine features to create any model and apply activation function like as softmax or sigmoid to classify the outputs as a car, dog, truck, etc.

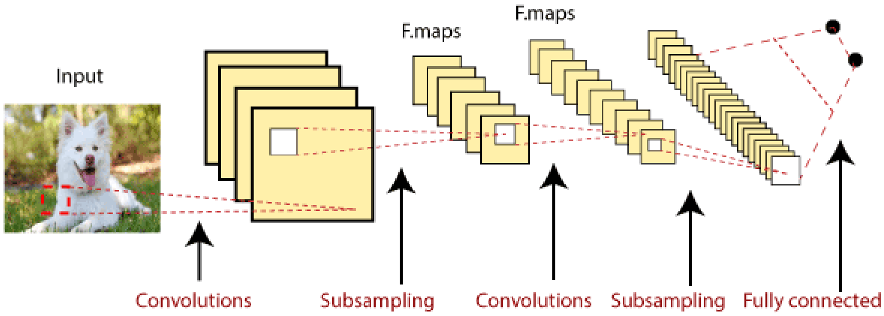


Figure 5.1.8: Classification

This is the final where the actual classification happens.

5.2Data Flow Diagram

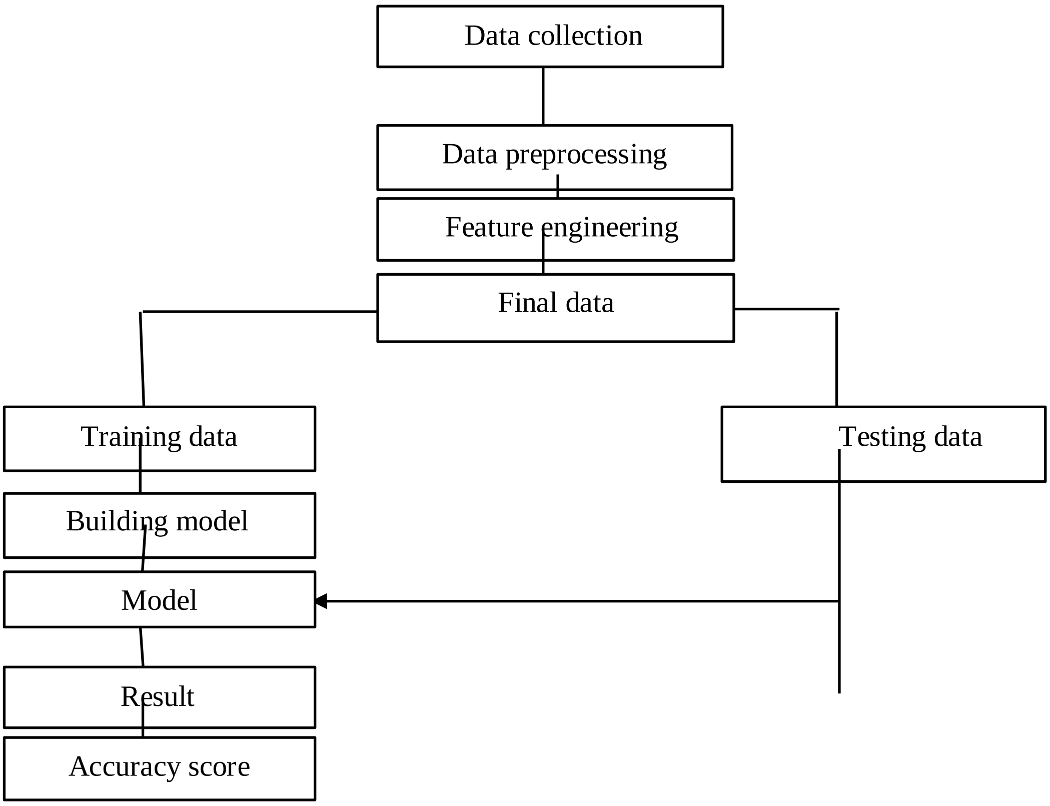


Figure 5.2.1: Data flow diagram

Figure 5.2.1 shows the data flow diagram of the system. The description of data flow diagram is given below:

Data Collection: As a society, we’re generating data at an unprecedented rate (see big data). These data can be numeric (temperature, customer retention rate), categorical (gender, color, highest degree earned), or even free text (think doctor’s notes or opinion surveys). Data collection is the process of gathering and measuring information from countless different sources. In order to use the data we collect to develop practical artificial intelligence (AI) and machine learning solutions.

Data preprocessing: Data preprocessing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data.

Feature engineering: Feature engineering or feature extraction is the process of using domain knowledge to extract features from raw data. The motivation is to use these extra features to improve the quality of results from a machine learning process, compared with supplying only the raw data to the machine learning process.

Final Data: Once feature extraction is done from raw data. Then useful data will be ready for further processing.

Training data: In machine learning, datasets are split into two subsets. The first subset is known as the training data - it's a portion of our actual dataset that is fed into the machine learning model to discover and learn patterns. Training data is the data you use to train an algorithm or machine learning model to predict the outcome you design your model to predict.

Testing Data: The other subset is known as the testing data. Test data is used to measure the performance, such as accuracy or efficiency, of the algorithm you are using to train the machine.

Model Building: The model building process involves setting up ways of collecting data, understanding and paying attention to what is important in the data to answer the questions you are asking, finding a statistical, mathematical or a simulation model to gain understanding and make predictions.

Model: A model represents what was learned by a machine learning algorithm. The model is the “thing” that is saved after running a machine learning algorithm on training data and represents the rules, numbers, and any other algorithm-specific data structures required to make predictions.

Result: Machine learning and artificial intelligence have achieved a human-level performance in many application domains, including image classification, speech recognition and machine translation.

Accuracy Score: Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations.

6.1 Execution Details

Our system is implemented by using :

1. HTML

HTML stands for Hyper Text Markup Language, which is the most widely used language on Web to develop web pages. HTML was created by Berners-Lee in late 1991 but "HTML 2.0" was the first standard HTML specification which was published in 1995. HTML 4.01 was a major version of HTML and it was published in late 1999. Though HTML 4.01 version is widely used but currently we are having HTML-5 version which is an extension to HTML 4.01, and this version was published in 2012.HTML stands for Hypertext Markup Language, and it is the most widely used language to write Web Pages.

2. CSS

CSS is used to control the style of a web document in a simple and easy way.CSS is the acronym for "Cascading Style Sheet". Cascading **S**tyle **S**heets, fondly referred to as CSS, is a simple design language intended to simplify the process of making web pages presentable.CSS handles the look and feel part of a web page. Using CSS, you can control the color of the text, the style of fonts, the spacing between paragraphs, how columns are sized and laid out, what background images or colors are used, layout designs, variations in display for different devices and screen sizes as well as a variety of other effects.CSS is easy to learn and understand but it provides powerful control over the presentation of an HTML document. Most commonly, CSS is combined with the markup languages HTML or XHTML.

3. JAVASCRIPT

JavaScript is a lightweight, interpreted programming language. It is designed for creating network-centric applications. It is complimentary to and integrated with Java. JavaScript is very easy to implement because it is integrated with HTML. It is open and cross-platform. JavaScript is a dynamic computer programming language. It is lightweight and most commonly used as a part of web pages, whose implementations allow client-side script to interact with the user and make dynamic pages. It is an interpreted programming language with object-oriented capabilities.

JavaScript was first known as LiveScript, but Netscape changed its name to JavaScript, possibly because of the excitement being generated by Java. JavaScript made its first appearance in Netscape 2.0 in 1995 with the name LiveScript. The general-purpose core of the language has been embedded in Netscape, Internet Explorer, and other web browsers.

4. BOOTSTRAP

Bootstrap is a free and open-source front-end web framework. It contains HTML and CSS-based design templates for typography, forms, buttons, navigation and other interface components, as well as optional JavaScript extensions. Unlike many earlier web frameworks, it concerns itself with front-end development only.Bootstrap is the third-most-starred project on GitHub, with more than 131,000 stars, behind only freeCodeCamp (almost 300,000 stars) and marginally behind Vue.js framework. According to Alexa Rank, Bootstrap getbootstrap.com is in the top-2000 in US while vuejs.org is in top-7000 in US.

5. PHP

The PHP Hypertext Preprocessor (PHP) is a programming language that allows wed developers to create dynamic content that interacts with databases. PHP is basically used for developing web based software applications. PHP started out as a small open source project that evolved as more and more people found out how useful it was. RasmusLerdorf unleashed the first version of PHP way back in 1994.

6. XAMPP

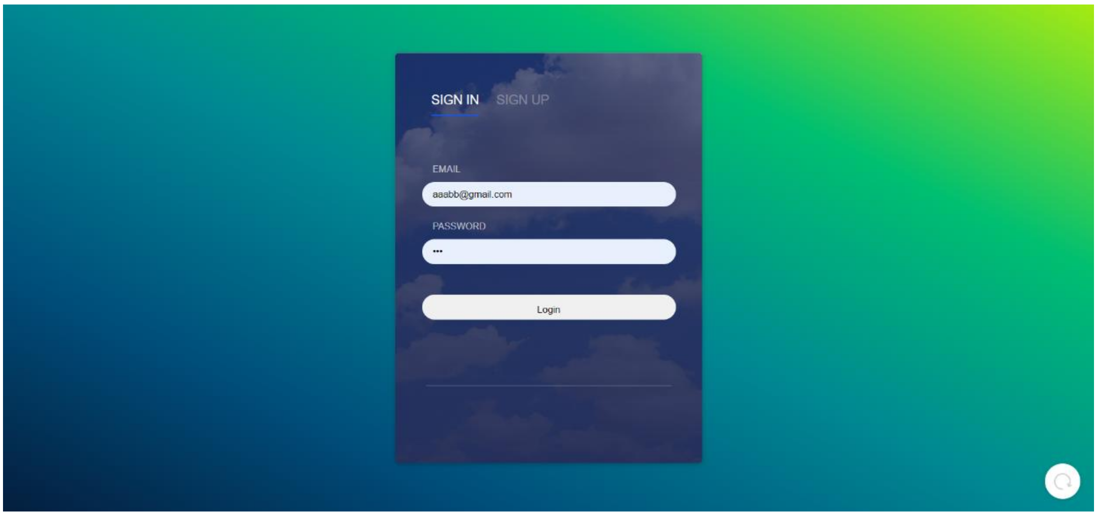
XAMPP is a free and open source cross-platform web server solution stack package, consisting mainly of the Apache HTTP Server, MySQL database, and interpreters for scripts written in the PHP and Perl programming languages XAMPP's name is an acronym for:

- X (to be read as "cross", meaning cross-platform)
- Apache HTTP Server
- MySQL

- PHP
- Perl

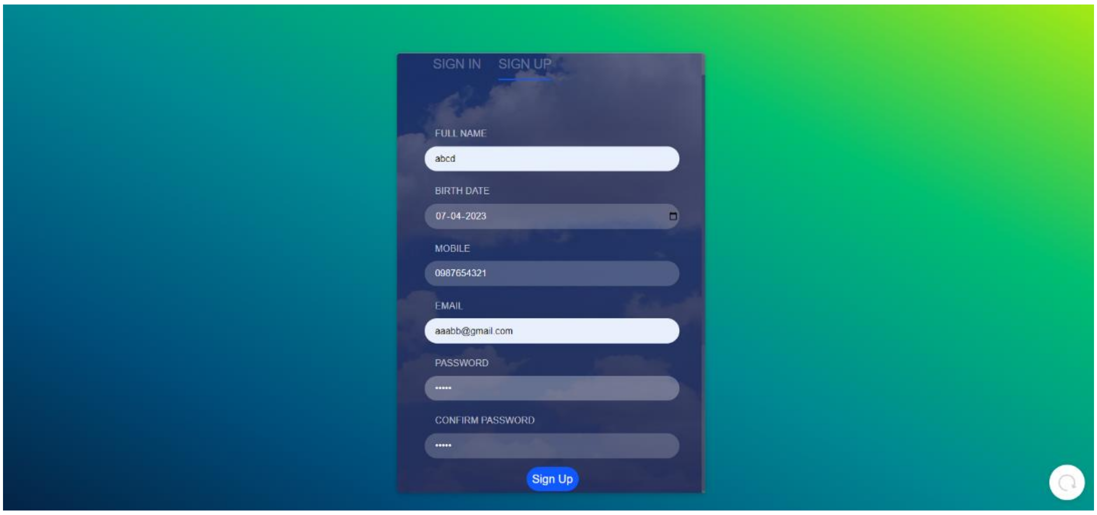
XAMPP requires only one zip, tar, 7z, or exe file to be downloaded and run, and little or no configuration of the various components that make up the web server is required. XAMPP is regularly updated to incorporate the latest releases of Apache, MySQL, PHP and Perl. It also comes with a number of other modules including OpenSSL and phpMyAdmin.Self-contained, multiple instances of XAMPP can exist on a single computer, and any given instance can be copied from one computer to another. It is offered in both a full, standard version and a smaller version. Officially, XAMPP's designers intended it for use only as a development tool, to allow website designers and programmers to test their work on their own computers without any access to the Internet. To make this as easy as possible, many important security features are disabled by default. In practice, however, XAMPP is sometimes used to actually serve web pages on the World Wide Web A special tool is provided.

6.2 Results



Screenshot 6.2.1: Login

Screenshot 6.2.1 shows Login page the user can sign in using the login credentials.

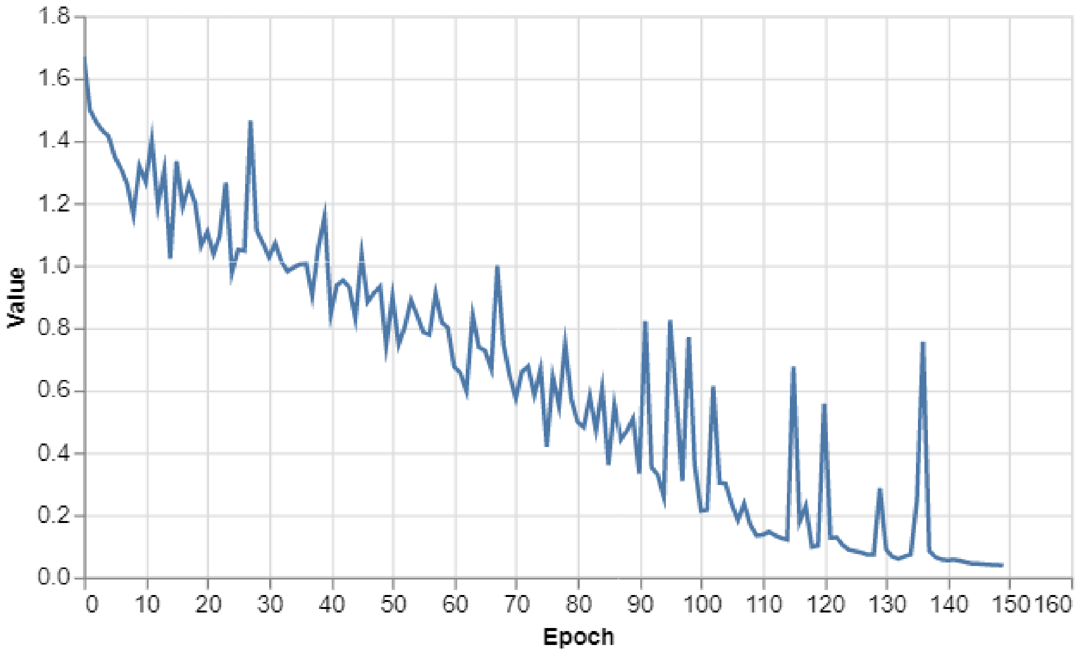


Screenshot 6.2.2: Registration

Screenshot 6.2.2 shows the registration page the new user can register by giving validate details of user for sign up.

Training Performance

onEpochEnd



Screenshot 6.2.3: Loss while training the system

Screenshot 6.2.3 shows Loss while training the system. The training loss is calculated over the entire training dataset. Train Error involves the human interpretable metric of your model's performance. Normally it means what percentage of training examples the model got incorrect.

Model Summary

Layer Name	Output Shape	# Of Params	Trainable
conv2d_Conv2D1	[batch,60,60,8]	808	true
max_pooling2d_MaxPooling2D1	[batch,30,30,8]	0	true
flatten_Flatten1	[batch,7200]	0	true
dense_Dense1	[batch,5]	36,005	true

Screenshot 6.2.4: Model Summary while training system

A Training Summary is an aggregate list of all of your professional development activities during a particular fiscal year. A Training Summary is extremely useful for both staff and supervisors when conducting an annual performance review.

Total number of Test images: 100

Predicted Value

Holy_Basil	Indian_CopperLeaf	Indian_Wormwood	Asthma_Plant	Indian_Sarsaparilla	Actual Value
20	0	0	0	0	Holy_Basil
8	12	0	0	0	Indian_CopperLeaf
1	0	19	0	0	Indian_Wormwood
11	0	0	8	1	Asthma_Plant
1	0	0	0	19	Indian_Sarsaparilla

Screenshot 6.2.5: Confusion Matrix while testing

A confusion matrix, in predictive analytics, is a two-by-two table that tells us the rate of false positives, false negatives, true positives and true negatives for a test or predictor. We can make a confusion matrix if we know both the predicted values and the true values for a sample set.

Accuracy: 0.7633587786259542

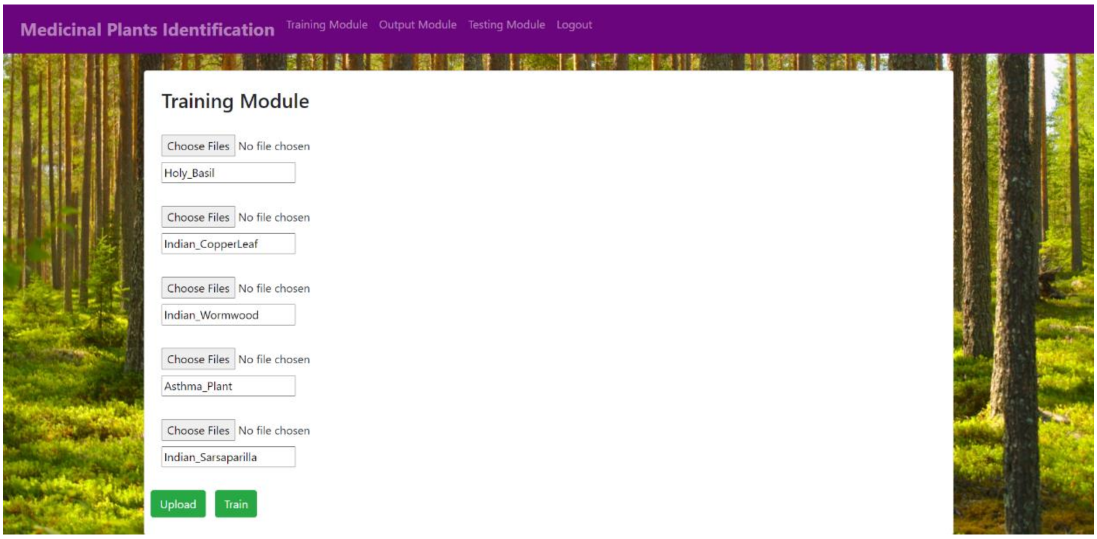
Precision: 0.7222222222222222

Recall: 0.9873417721518988

F1 Score: 0.8342245989304813

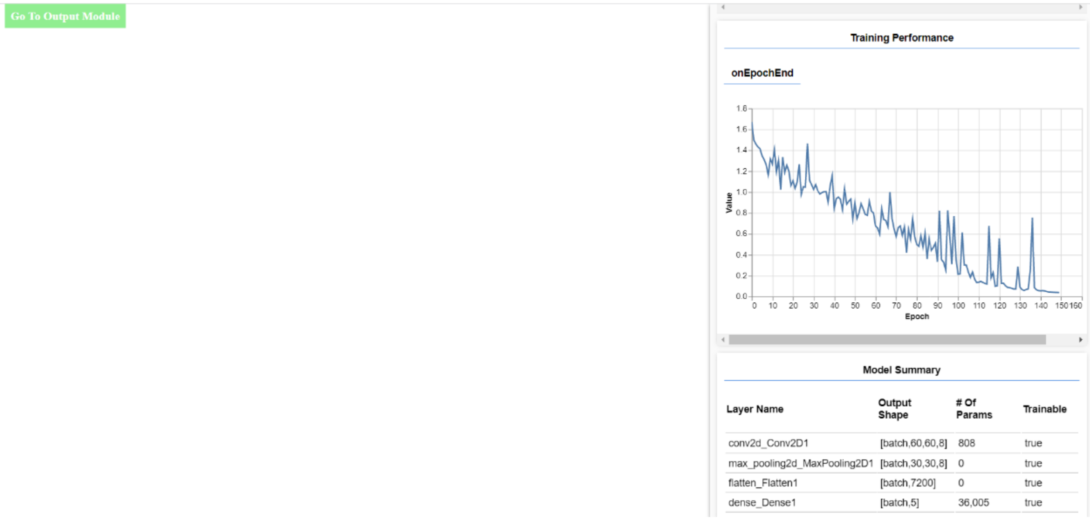
Screenshot 6.2.6: Accuracy of CNN Algorithm

Screenshot 6.2.6 shows Accuracy of CNN Algorithm Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations.



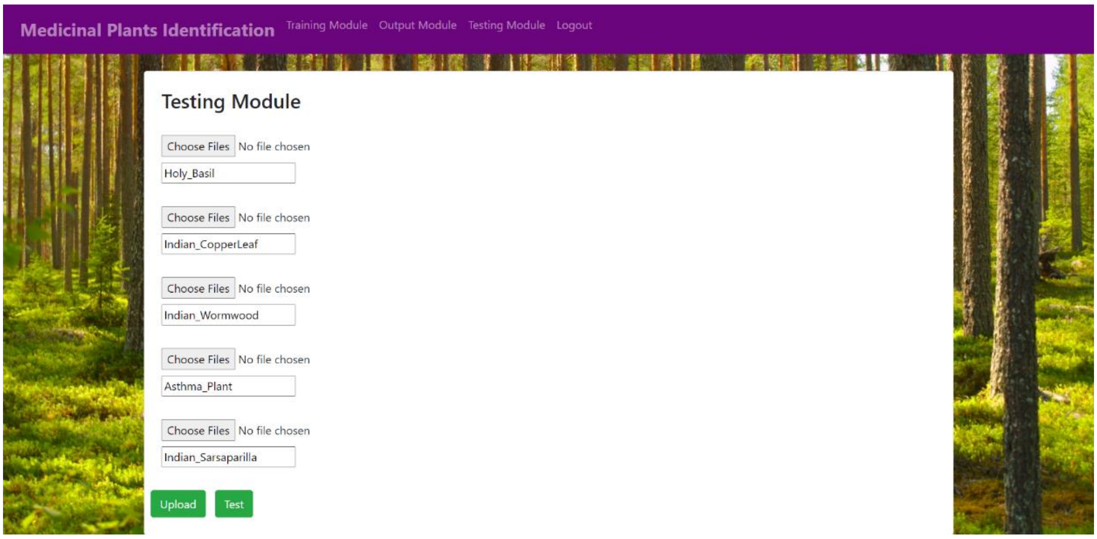
Screenshot 6.2.7: Training Module

Screenshot 6.2.7 shows the user interface of training module.



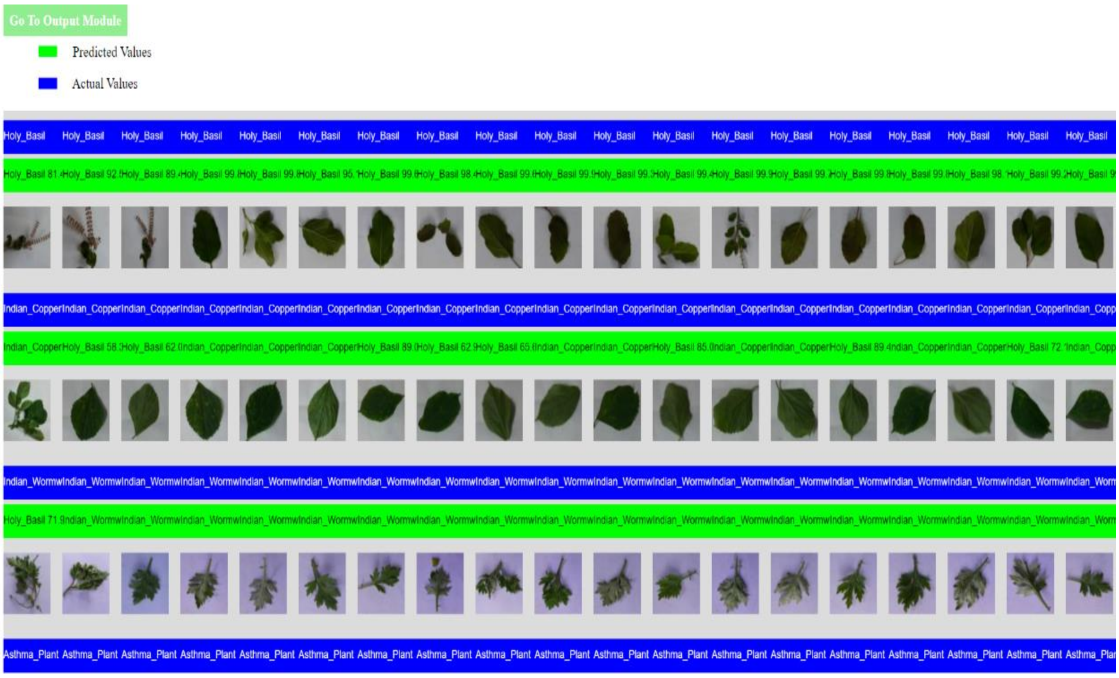
Screenshot 6.2.8: Training Page

Screenshot 6.2.8 shows Training Page. Training data is the data you use to train an algorithm or machine learning model to predict the outcome you design your model to predict.



Screenshot 6.2.9 Testing Module

Screenshot 6.2.9 shows the user interface of testing module.

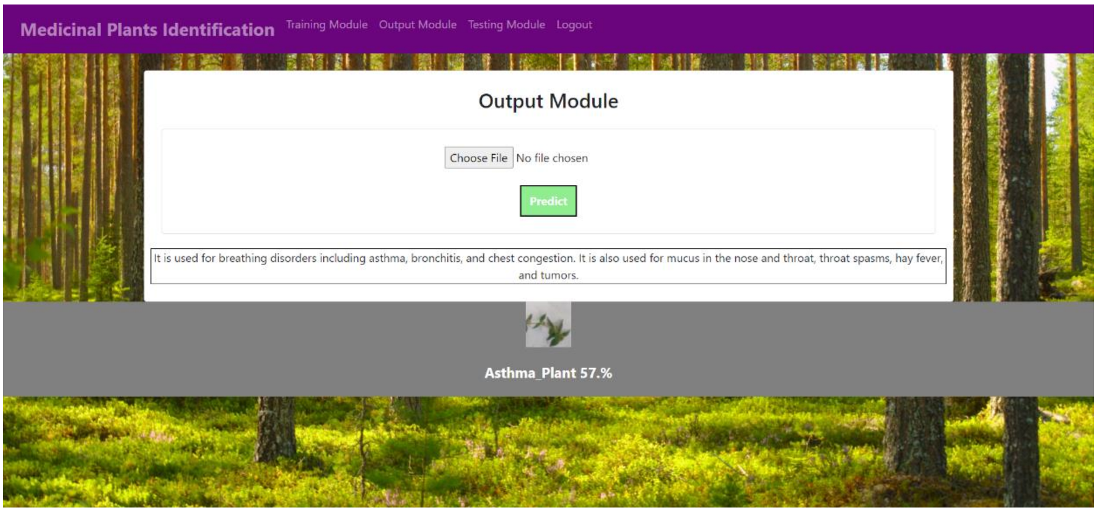


Screenshot 6.2.10 Testing Page

Holy_Basil	Indian_CopperLeaf	Indian_Wormwood	Asthma_Plant	Indian_Sarsaparilla	
20	0	0	0	0	Holy_Basil
8	12	0	0	0	Indian_CopperLeaf
1	0	19	0	0	Indian_Wormwood
11	0	0	8	1	Asthma_Plant
1	0	0	0	19	Indian_Sarsaparilla

Screenshot 6.2.11 Testing Page

Screenshot 6.2.10 & 6.8.11 shows Testing Page. Test data is used to measure the performance, such as accuracy or efficiency, of the algorithm you are using to train the machine.



Screenshot 6.2.12: Output Module

Screenshot 6.2.12 shows Output Module. This page can choose image and identify the Plant.

7.1 Conclusion

The implementation of medicinal plant identification using deep learning. Provided sufficient data is available for training, deep learning techniques are capable of identifying medicinal plants with high accuracy. The importance of collecting large datasets with high variability, data augmentation, transfer learning, and visualization of CNN activation maps in improving classification accuracy, and the importance of small sample medicinal plant identification and the importance of hyper-spectral imaging for early identification of medicinal plant have been discussed.

7.2 Future Scope

In most of the researches, the Plant Village dataset was used to evaluate the performance of the DL models. Although this dataset has a lot of images of several plant species with their medicinal use, it was taken in the lab. Therefore, in future it is expected to establish a large dataset of medicinal plant in real condition.

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