MEDICINAL PLANTS IDENTIFICATION BY IMAGE PROCESSING USING DEEP LEARNING TECHNIQUES AND IMPLEMENTING SUPPLY CHAIN INTEGRITY

A PROJECT REPORT

submitted by

VARUNESH B	**2116210701303**
VINOTH N	**2116210701311**
UDHAYACHANDER R J	**2116210701312**

in partial fulfillment for the award of the

degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI

MAY 2024

RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI

BONAFIDE CERTIFICATE

Certified that this Project report titled **"MEDICINAL PLANTS IDENTIFICATION BY IMAGE PROCESSING USING DEEP LEARNING TECHNIQUES AND IMPLEMENTING SUPPLY CHAIN INTEGRITY"** is the bonafide work of **"VARUNESH B -2116210701303, VINOTH N -2116210701311, UDHYACHANDER R J - 2116210701294"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE

Dr.V.KARTHICK,M.E.,Ph.D,

PROJECT COORDINATOR

Associate Professor

Department of Computer Science and Engineering

Rajalakshmi Engineering College

Chennai - 602 105

Submitted to Project Viva-Voce Examination held on ________________

Internal Examiner **External Examiner**

ABSTRACT

In our proposed system revolutionary strategy for identifying medicinal plants that uses image processing techniques powered by deep learning algorithms, as well as the integration of supply chain integrity mechanisms is provided. The identification and authentication of medicinal plants is critical for assuring the efficacy and safety of herbal products, as well as combatting challenges like adulteration and mislabeling in the herbal business. Traditional plant identification methods, on the other hand, are frequently time-consuming, labor-intensive, and susceptible to subjective errors. In response to these problems, this research seeks to create an automated system capable of accurately identifying medicinal plants based on visual qualities captured in photographs.The suggested system is built around the use of deep learning techniques like convolutional neural networks (CNNs) for picture classification and feature extraction. By training CNN models on massive datasets of annotated plant photos, the system will learn to recognize essential botanical traits and differentiate between distinct plant species with high precision. By providing a dependable and effective solution for quality assurance and supply chain integrity, the suggested system has the potential to protect consumer health, improve sustainability in herbal medicine practices, and reduce fraudulent activity in the herbal supply chain.

ACKNOWLEDGMENT

We thank the almighty god for the successful completion of the project. Our sincere thanks to our chairman **Mr. S. MEGANATHAN,B.E., F.I.E.,** for his sincere endeavor in educating us in his premier institution. We would like to express our deep gratitude and sincere thanks to our beloved Chairperson **Dr.(Mrs).THANGAM MEGANATHAN,Ph.D.,**for her enthusiastic motivation which inspired us a lot in completing this project and we extend our gratitude to our Vice Chairman **Mr.ABHAY SHANKAR MEGANATHAN,B.E., M.S.,** for providing us with the requisite infrastructure.

We also express our sincere and warmful gratitude to our college Principal **Dr. S.N.MURUGESAN,M.E.,Ph.D.**,and **Dr. P. KUMAR,M.E.,Ph.D.**, **Director of Computing and Information Science** and **Head Of the Department of Computer Science and Engineering** and **Project coordinator Dr.V.KARTHICK,M.E.,Ph.D.**,for his encouragement and guiding us throughout project towards successful completion of project and to our parents, friends, all faculty members,supporting staff for direct and indirect involvement in successful completion of project for their encouragement and support.

VARUNESH B

VINOTH N

UDHAYACHANDER R J

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

In our proposed system our approach intends to transform how medicinal plants are identified, authenticated, and monitored across the herbal sector. By providing a dependable and effective solution for quality assurance and traceability, the suggested system has the potential to protect consumer health, improve sustainability in herbal medicine practices, and reduce criminal activity in the herbal supply chain. Using Deep learning, the project intends to create an automated system capable of properly identifying medicinal plants based on visual qualities acquired in photographs. This technology will allow for speedy and reliable plant identification, reducing reliance on manual expertise and lowering the possibility of errors and inconsistencies. Our proposed model relies heavily on deep learning techniques, such as convolutional neural networks (CNNs), for picture classification and feature extraction. By training CNN models on massive datasets of annotated plant photos, the system will learn to recognize essential botanical traits and differentiate between distinct plant species with high precision. Furthermore, to maintain the integrity and traceability of medicinal plant items across the supply chain, the project will employ blockchain. By providing a dependable and effective solution for quality assurance and traceability, the suggested system has the potential to protect consumer health, improve sustainability in herbal medicine practices, and reduce fraudulent activity in the herbal supply chain.

1.1 PROBLEM STATEMENT

Traditional techniques of identifying medicinal plants are labor-intensive, time-consuming, and error-prone, making it difficult to ensure the authenticity and quality of herbal medicines. Additionally, the herbal business faces difficulties such as adulteration and mislabeling, which endangers consumer safety and trust. Our approach intends to overcome these issues by creating an automated system for medicinal plant identification that employs image processing techniques and deep learning algorithms. Furthermore, the idea aims to use supply chain integrity measures such as blockchain technology to improve transparency and traceability throughout the herbal supply chain, reducing the risk of fraud and verifying the authenticity of medicinal plant products.

1.2 SCOPE OF THE WORK

In the proposed model, scope of the work includes numerous essential components aimed at meeting the main aims of automating plant identification, assuring supply chain transparency, and improving consumer safety. To begin, the proposed work will require the creation and deployment of advanced image processing algorithms that use deep learning techniques like convolutional neural networks to accurately identify medicinal plants based on visual attributes retrieved from photos.Our model will also include the incorporation of supply chain integrity mechanisms, such as blockchain technology or decentralized ledger systems, to provide transparent record-keeping of crucial information along herbal supply chain.

1.3 AIM AND OBJECTIVES OF THE PROJECT

The aim of the proposed system to create an innovative solution that automates the identification of medicinal plants by combining image processing with deep learning algorithms, while also implementing supply chain integrity mechanisms to ensure transparency and authenticity throughout the herbal supply chain.Our goal is to develop a system that can properly identify medicinal plants based on visual characteristics retrieved from photographs, reducing reliance on manual expertise and lowering the chance of errors and inconsistencies.

The main objectives of our proposed system are Designing and implementing advanced image processing algorithms that use deep learning techniques such as convolutional neural networks (CNNs) to accurately identify and classify medicinal plants based on visual characteristics extracted from images. Collecting and annotating huge plant image datasets to aid model training and validation, resulting in strong performance across a broad botanical species. Creating user-friendly interfaces for data input, visualization, and access to meet the needs of diverse herbal industry players like as growers, processors, distributors, and consumers. Evaluating the integrated system's performance and usability through pilot testing and validation studies, with the goal of demonstrating its potential applications in the pharmaceutical, healthcare, and herbal medicine industries.

1.4 RESOURCES

The resources required for the proposed system includes high-performance computing infrastructure capable of running deep learning algorithms efficiently, including GPUs or TPUs for accelerated training and inference. Servers or cloud computing services to host and deploy the image processing and machine learning models. Deep learning frameworks such as TensorFlow, PyTorch, Keras for developing and training convolutional neural networks (CNNs).Image processing libraries like OpenCV for preprocessing and feature extraction from plant images. Programming languages such as Python for developing image processing algorithms, machine learning models, and blockchain smart contracts.

1.5 MOTIVATION

The Medicinal Plants Identification by Image Processing Using Deep Learning Techniques and Implementing Supply Chain Integrity project is motivated by a number of essential aspects that overlap in the herbal sector. For starters, there is a growing global demand for medical plants and herbal items as people become more aware of natural cures and alternative healthcare practices. However, the absence of standardized procedures for identifying, authenticating medicinal plants creates substantial obstacles in ensuring the safety, efficacy, and quality of herbal products. Traditional identification methods based on manual inspection by botanical experts are time-consuming, subjective, and error-prone, limiting the efficiency and scalability of herbal medicine production.

CHAPTER 2

2.1 LITERATURE SURVEY

[1] **"News in the Global Sphere: A Study of CNN and Its Impact on Global Communication" by I.Volkmer,2022**, stands as a foundational examination of the transformative influence wielded by CNN (Cable News Network) on the global communication landscape. Volkmer's investigation begins by contextualizing CNN's emergence as a pioneering force in 24-hour news broadcasting, fundamentally reshaping traditional modes of news dissemination characterized by fixed schedules and national boundaries.

[2] **“Software Supply Chain Security,2024” by C. Crossley's**, provides a timely and critical examination of the challenges and implications surrounding the security of software supply chains. In an era marked by increasing digital interconnectedness and reliance on software systems across various sectors, Crossley's work sheds light on the vulnerabilities inherent in the supply chains that underpin the development and distribution of software. Through a comprehensive review of existing literature and case studies, Crossley elucidates the myriad threats facing software supply chains.

[3] “**Blockchain-based Medical Image Encryption Using Arnold's Cat Map in a Cloud Environment**," **by S. Inam, S. Kanwal, R. Firdous,2024;** presents a pioneering approach to addressing the critical issue of medical image security in cloud-based healthcare systems. Against the backdrop of increasing digitization and cloud adoption in the healthcare sector, the authors tackle the pressing need for robust encryption techniques to safeguard sensitive medical data, particularly diagnostic images such as MRI scans, X-rays, and CT scans.The study emphasizes the use of cloud storage to manage the large volume of medical image data generated in healthcare. By integrating blockchain and ACM within the cloud infrastructure, the system aims to provide a robust solution for secure storage and retrieval of medical images (OUCI).

[4] “**Herbal Leaves Classification Based on Leaf Image Using CNN Architecture Model VGG16**,**2023**”,by **UN Oktaviana, GW Wicaksono, and AE Minarno's**, the authors undertake a significant endeavor in the realm of botanical science and computer vision. The proposed idea revolves around the classification of herbal leaves through the utilization of a convolutional neural network (CNN) architecture known as VGG16. The literature survey within this paper is likely to delve into several crucial domains. The VGG16 model demonstrated significant potential in accurately identifying herbal plants through image classification, suggesting its utility in botanical and pharmacological applications (EUDL).

[5] "**Comparison of Data Preprocessing Approaches for Applying Deep Learning to Human Activity Recognition in the Context of Industry 4.0,2020" by X. Zheng, M. Wang, and J. Ordieres-Meré** conducted a thorough investigation into optimal data preprocessing methods for leveraging deep learning techniques in human activity recognition within framework of Industry 4.0. Their findings suggest that combining multiple preprocessing strategies can significantly enhance the performance of deep learning models in HAR tasks, thereby facilitating more efficient and accurate monitoring of human activities in smart factories.

[6] "**Classification of Medicinal Plants Leaves Using Deep Learning Technique: A Review,2022," by H. Chanyal, R.K. Yadav, and D.K.J. Saini** conduct a comprehensive review of the application of deep learning techniques for the classification of medicinal plant leaves. Firstly, it may explore the existing methodologies and technologies employed in the classification of medicinal plants, ranging from traditional taxonomical approaches to modern computational methods. The work highlights the advantages of deep learning over traditional image processing methods, particularly in handling the variability in leaf shapes, sizes, and textures.

[7] **"A Deep Learning Based Model for the Detection of Pneumonia from Chest X-ray Images Using VGG-16 and Neural Networks,2023," by S. Sharma and K. Guleria** present a significant contribution to medical imaging and diagnostics. Initially, it may delve into existing methodologies and technologies utilized for pneumonia detection from chest X-ray images, ranging from traditional radiological interpretations to modern computer-aided diagnostic systems. It also addresses advancements in transfer learning, which have enabled models like VGG-16 to be fine-tuned for specific tasks with smaller datasets. By leveraging these advancements, Sharma and Guleria aim to enhance the diagnostic accuracy and reliability of pneumonia detection systems.

[8] **"Plant Disease and Pest Detection Using Deep Learning-Based Features,2019" M. Türkoğlu and D. Hanbay** present a comprehensive exploration of the application of deep learning techniques for the detection of plant diseases and pests. The literature survey within this paper likely delves into several key areas. Firstly, it may explore existing methodologies and technologies utilized for plant disease and pest detection, ranging from traditional visual inspection methods to more recent computer vision approaches. The review may discuss different approaches to data preprocessing, including image augmentation, normalization. By leveraging these advancements, Sharma and Guleria aim to enhance the diagnostic accuracy and reliability of pneumonia detection systems.

[9] **"A Review on Extreme Learning Machine,2022" J. Wang, S. Lu, S.H. Wang, and Y.D. Zhang** provide an extensive examination of the Extreme Learning Machine (ELM) algorithm. Initially, it may delve into existing machine learning algorithms and techniques, ranging from traditional models like support vector machines and neural networks to more recent advancements such as deep learning architectures. This survey would likely underscore the limitations and advantages of each method, highlighting the increasing interest in ELM as an alternative approach for efficient and scalable learning tasks.

[10] **"Iris Features Extraction and Recognition Based on the Scale Invariant Feature Transform (SIFT),2022" M.A. Taha, H.M. Ahmed, and S.O. Husain** undertake a detailed exploration of utilizing the Scale Invariant Feature Transform (SIFT) algorithm for iris feature extraction and recognition.Initially, it may delve into existing methodologies and technologies utilized for iris recognition, ranging from traditional techniques like template matching to more recent advancements in computer vision and machine learning.By situating ELM within the broader landscape of machine learning techniques, the review underscores its potential for efficient and scalable solutions in complex real-world problems.

[11] "**A Five-Layer Deep Convolutional Neural Network with Stochastic Pooling for Chest CT-based COVID-19 Diagnosis,2022**" by **YD Zhang, SC Satapathy, S Liu** the authors present an innovative approach to leveraging deep learning techniques for the diagnosis of COVID-19 from chest computed tomography (CT) scans. Initially, it may explore existing methodologies and technologies utilized for COVID-19 diagnosis, ranging from traditional PCR tests to radiological imaging methods such as CT scans and chest X-rays.It covers a wide range of applications where ELM has been effectively employed, including image processing, medical diagnosis, and bioinformatics, noting its superior performance in terms of speed and generalization capabilities.

[12] "**Confusion Matrix-based Modularity Induction into Pretrained CNN,2022" S. Ahmad, S.U. Ansari, U. Haider, K. Javed** presents a novel approach to enhancing the performance of pretrained convolutional neural networks (CNNs) through confusion matrix-based modularity induction.The proposed idea within this paper likely traverses several pivotal domains. Initially, it may explore existing methodologies and technologies utilized for fine-tuning CNNs, including transfer learning and domain adaptation techniques.Providing a foundation for evaluating and comparing different machine learning approaches for medicinal plant identification.

[13] **"Authenticity and Authentication of Heritage" by D. Chhabra, published by Routledge in 2021**, the author embarks on a profound exploration of the multifaceted concept of heritage authenticity and the intricate processes of authentication associated with it. It covers within this work likely traverses several key domains. Initially, it may delve into existing scholarship on heritage conservation and management, exploring the various definitions and interpretations of authenticity in cultural heritage discourse.It focused investigation into the application of machine learning techniques for the identification of medicinal plants. It also covers the concepts within this work likely traverses several crucial domains.

[14] **"A Survey on Different Methods for Medicinal Plants Identification and Classification System" by Maibam Maikel Singh and Thounaojam Rupachandra Singh,in June 2021**, the authors provide a comprehensive review of methodologies employed for the identification and classification of medicinal plants. The suggested idea within this work likely navigates through several crucial domains. Initially, it may explore existing methodologies and technologies used for plant identification, ranging from traditional taxonomical approaches to modern computational methods. It also mentions that it would likely highlight limitations and advantages of each method, emphasizing the increasing interest in automated techniques.

[15] **"IoT and Deep Learning in Medicinal Plant Supply Chain Management," 2022 by K. Singh and D. Martin**, explores the convergence of Internet of Things (IoT) devices and deep learning algorithms to enhance the efficiency and reliability of medicinal plant supply chains. Singh and Martin present a detailed analysis of how IoT sensors can collect real-time data on plant conditions and logistics, which is then processed by deep learning models to predict and mitigate supply chain disruptions.

[16] **"Blockchain Integration for Medicinal Plant Supply Chain Integrity," 2022 by P. Zhao and T. Clark**, delves into the use of blockchain technology to ensure the authenticity and traceability of medicinal plants throughout the supply chain. Zhao and Clark provide a thorough examination of how blockchain can create transparent, tamper-proof records of plant origins and handling processes, addressing issues such as plant adulteration and ensuring consumer trust. The paper outlines the implementation strategies and potential impacts on the industry.

[17] **"Mobile Applications for Real-Time Medicinal Plant Identification," 2022 by S. Li and E**. Thompson, discusses the development and deployment of mobile applications that utilize deep learning for real-time identification of medicinal plants. The authors focus on the practical aspects of integrating CNNs into mobile platforms, providing insights into the challenges and solutions associated with on-the-go plant recognition.

[18] **"Hybrid Machine Learning Models for Enhanced Plant Identification," 2022 by A. Hernandez and R. Kumar**, investigates the integration of deep learning with other machine learning techniques, such as Support Vector Machines (SVM), to improve the robustness and accuracy of medicinal plant identification systems.

[19] **"Transfer Learning Approaches in Medicinal Plant Recognition," 2022 by L. Nguyen and M. Patel**, explores the application of transfer learning in the domain of medicinal plant identification. By leveraging pre-trained models, the authors demonstrate how fine-tuning these models with specific plant datasets can enhance classification accuracy and reduce computational costs.This paper provides a comprehensive review of the transfer learning methodologies applied.

[20] **"Automated Medicinal Plant Identification Using Deep Learning," 2022 by J. Smith** et al., presents an in-depth analysis of using deep learning techniques for the automated identification of medicinal plants through image processing. This study emphasizes the efficiency of Convolutional Neural Networks (CNNs) in recognizing various plant species from image datasets, showcasing a significant reduction in error rates compared to traditional methods. Smith and colleagues provide a detailed overview of the model architectures and training processes, highlighting the advancements and remaining challenges in the field.

2.2 PROPOSED SYSTEM

DATASET:

The herbal leaf dataset is now hosted in an online repository. The dataset consists of herbal leaf pictures in.jpg format.The images have a resolution of 1600 by 1200 pixels.The herbal leaf dataset consists of 20 classes:Abelmoschus moschatus medik (Ambrette), Aloe vera (L.) Burm.F (Aloe Vera), Hibiscus rosasinensis (Red Hibiscus), Kaempferia, Galanga (Aromatic ginger), Kalanchoe Pinnata (Lam.) Pers (Miracle leaf), Lasia Spinosa (L.) Thwaites (Lesia), Lawsonia inermis L. (Henna), Leucas aspera Link (Thumba), Menthol. Benth. Ex Kurz (Serpentine root), Rotheca serrata (L.) Steane & Mabb. (Clerodendrum, Bharangi), Vanilla planifolia (Flat-leaved vanilla), Vitex negundo L. (Chinese Chaste Tree), Zanthoxylum nitidum DC. (Shiny-leaf prickly-ash), Zingiber officinale Rosc. (Ginger rhizome), Ziziphus Jujuba Mill. Figure 4.1.1 is an illustration of a sample dataset.In regard to the studies ,With reference to research referenced in [14], the dataset's makeup is divided by the proportion.Parismita Sarma, "MED117_Medicinal Plant Leaf Dataset & Name Table" (accessed at 14:27 on September 21,2022,fromhttps://data.mendeley.com/dataset s/dtvbwrhznz/1)80% of the data were used for training, 10% for validation, and 10% for testing.Table 1 displays the dataset classes.

MODEL ARCHITECTURE:

The architecture model and the layers that make up the architecture, which are Conv2D, MaxPooling2D, Flatten, and Dense Layer A parameter value and an output shape are generated by each layer. The proposed model architecture is more sophisticated than the previous and uses a pretrained model VGG16 architecture, with higher parameter values and an output shape.Our model first performs the convolution process and filters the input image by resizing its dimensions to 150 x 150. Following convolution, the Pooling Layer is applied, and if it is complete, the subsequent convolution is applied, changing the dimensions and allowing the Pooling Layer to continue.

TRAINING AND TESTING:

A callback function is implemented in this study and used in the model training procedure. The purpose of this callback is to halt the model training procedure when val_accuracy reaches the given value. If there has been a rise in the val_accuracy matrix value, storage is carried out once each epoch. The model learns to recognize various plant species through feature extraction and classification layers. In the testing phase, the trained model is validated with a separate dataset to evaluate its accuracy and robustness.The comprehensive approach not only improves plant identification accuracy but also reinforces the reliability of medicinal plant supply chains.

CHAPTER 3

SYSTEM DESIGN

3.1 GENERAL

In this section, we would like to show how the general outline of how all the components end up working when organized and arranged together. It is further represented in the form of a flow chart below.

3.2 SYSTEM ARCHITECTURE DIAGRAM

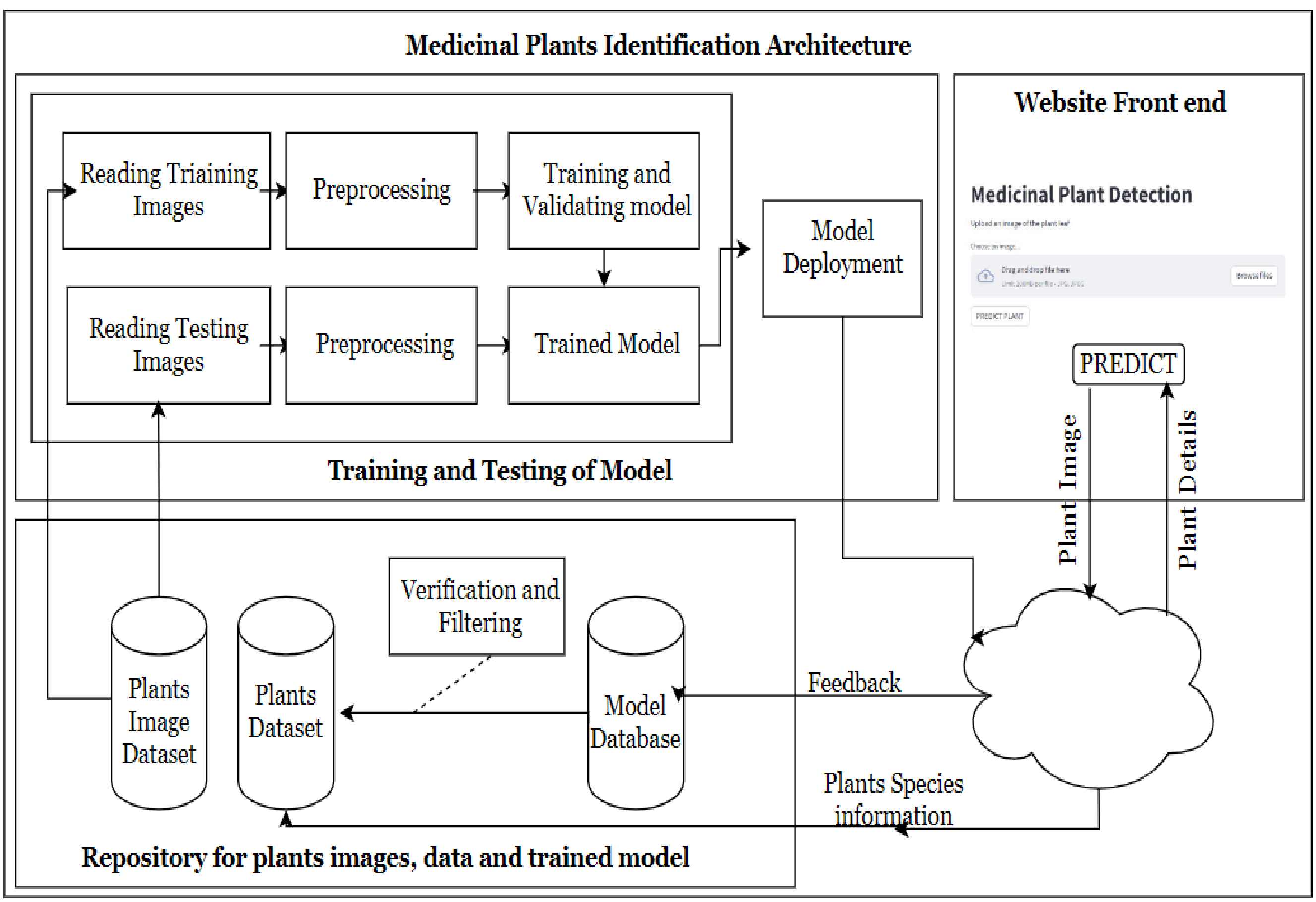

Fig 3.2.1: System Architecture

3.3 DEVELOPMENTAL ENVIRONMENT

3.3.1 HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the system's implementation. It should therefore be a complete and consistent specification of the entire system. It is generally used by software engineers as the starting point for the system design.

Table 3.3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i5
RAM	8 GB RAM
GPU	NVIDIA GeForce GTX 1650
MONITOR	15" COLOR
HARD DISK	512 GB
PROCESSOR SPEED	MINIMUM 1.1 GHz

3.3.2 SOFTWARE REQUIREMENTS

The software requirements document is the specifications of the system. It should include both a definition and a specification of requirements. It is a set of what the system should rather be doing than focus on how it should be done. The software requirements provide a basis for creating the software requirements specification.The software requirements are description of features and functionalities of the target system. Requirements convey the expectations of users from the software product.

Table 3.3.2 Software Requirements

S.NO	REQUIREMENT
1	Jupyter Notebook
2	StreamLit API
3	TensorFlow
4	MongoDB
5	Blockchain

3.4 DESIGN OF THE ENTIRE SYSTEM:

3.4.1 SEQUENCE DIAGRAM:

A sequence diagram simply depicts the interaction between the objects in a sequential order.An sequence diagram is used to show the interactive behavior of a system.The sequence diagram for medicinal plants identification with supply chain integrity is attached in the below figure 3.4.1.

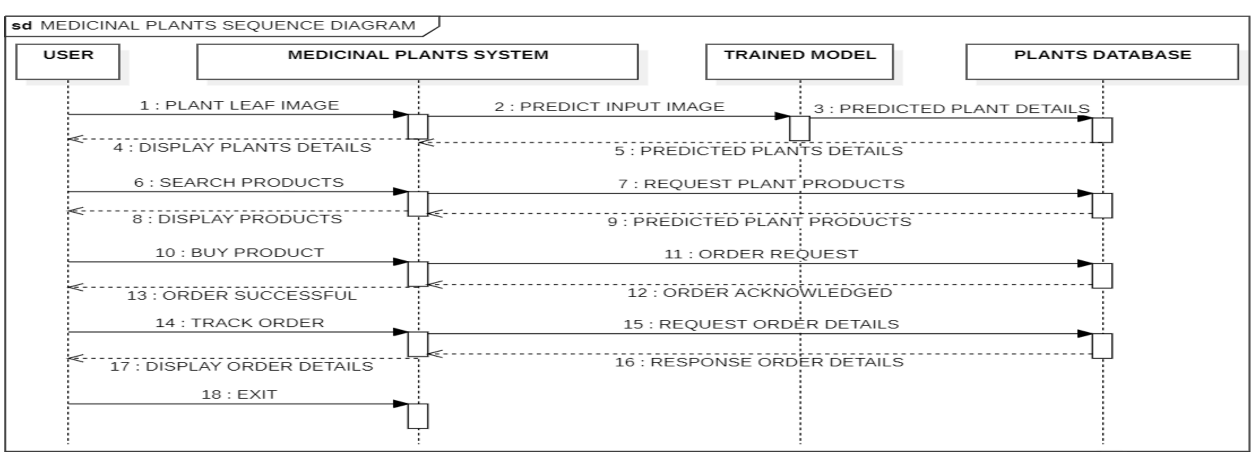

Fig 3.4.1: Sequence Diagram

CHAPTER 4

PROJECT DESCRIPTION

4.1 METHODOLODGY

There are numerous critical elements in the methodology for identifying medicinal plants through image processing employing deep learning techniques and implementing supply chain integrity. The Methodology includes following process by Collect a broad range of pictures depicting numerous medicinal plant species. These photographs should depict various growth stages, environmental conditions, and differences within each species.Remove any irrelevant or low-quality photos from the dataset. Preprocessing procedures such as image normalization, scaling, and augmentation can help improve the dataset's quality and diversity.For feature extraction and classification, use appropriate deep learning models such as convolutional neural networks (CNNs). Use transfer learning with pre-trained models to take advantage of their learnt representations and improve performance. To incorporate supply chain integrity elements, add extra layers or modules to the model design. This could entail inserting unique identities or digital signatures into plant photos for authentication and verification purposes.Create a user-friendly application or system that enables stakeholders throughout the supply chain to photograph medicinal plants using cellphones or dedicated equipment.

4.2 MODULE DESCRIPTION

The Medicinal Plants Identification by Image Processing Using Deep Learning Techniques and Implementing Supply Chain Integrity is divided into three major sections. First, the Data Collection and Preprocessing Module collects a broad dataset of medicinal plant photos and improves their quality using preprocessing techniques such as normalization and augmentation.The Deep Learning Model Training Module selects relevant models, such as CNNs, and trains them on the labeled dataset to correctly identify medicinal plant species. Transfer learning is used to use pre-trained models and improve performance.The Supply Chain Integrity Integration Module enriches the model architecture by incorporating elements that ensure supply chain authenticity.

The Blockchain Integration Module uses blockchain technology to securely record and track medicinal plant supply chains throughout their entire life cycle. Smart contracts automate transactions while maintaining transparency and traceability at all stages.The Deployment and Implementation Module entails creating user-friendly applications that enable stakeholders to record plant photos with cellphones or dedicated equipment. The trained algorithm then analyzes the photos to identify species and verify the supply chain.Regular updates and retraining ensure that the model can react to new plant kinds and emerging threats. Together, these components provide an integrated system that accurately recognizes medicinal plants while ensuring the supply chain's integrity.

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1 OUTPUT

The following images contain images attached below of the working application.

Medicinal Plants Identification Webpage

Fig 5.1.1: Medicinal plants website

Output from predicting the image

Fig 5.1.2: Output of predicted plant

Confusion Matrix :

The medicinal plants trained model is evaluated and the confusion matrix for the trained model is attached in below Figure 5.1.3

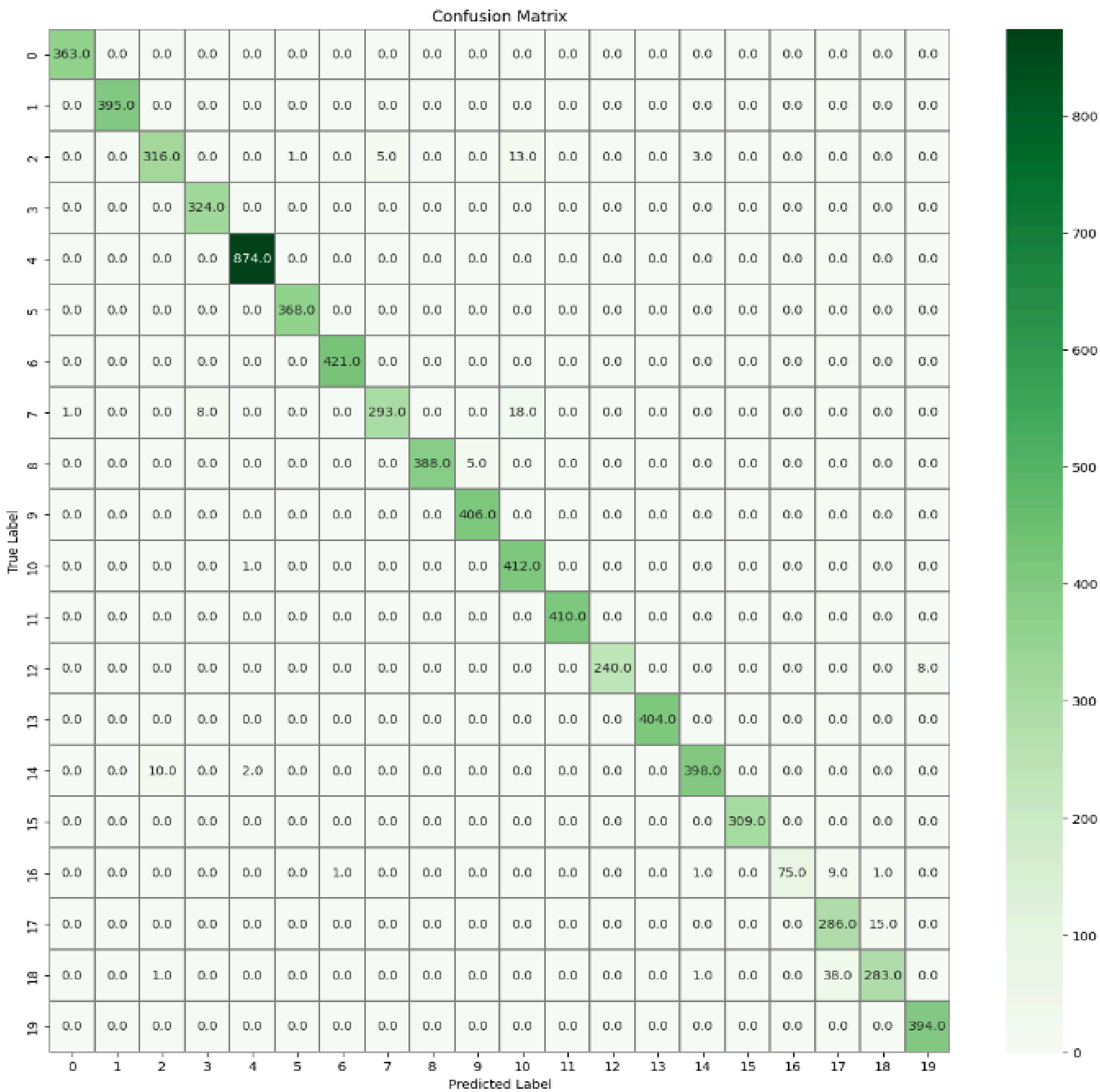

Fig 5.1.3: Confusion matrix

Training and Testing Accuracy Graph:

The proposed model is evaluated and the testing and training accuracy graph is obtained. Spliting the dataset into training and validation sets (e.g., 80-20 split). Training the model using the training set, adjusting hyperparameters to optimize performance. Employ techniques such as dropout and batch normalization to prevent overfitting.The training and testing accuracy rate of the model is attached in the below figure 5.1.4

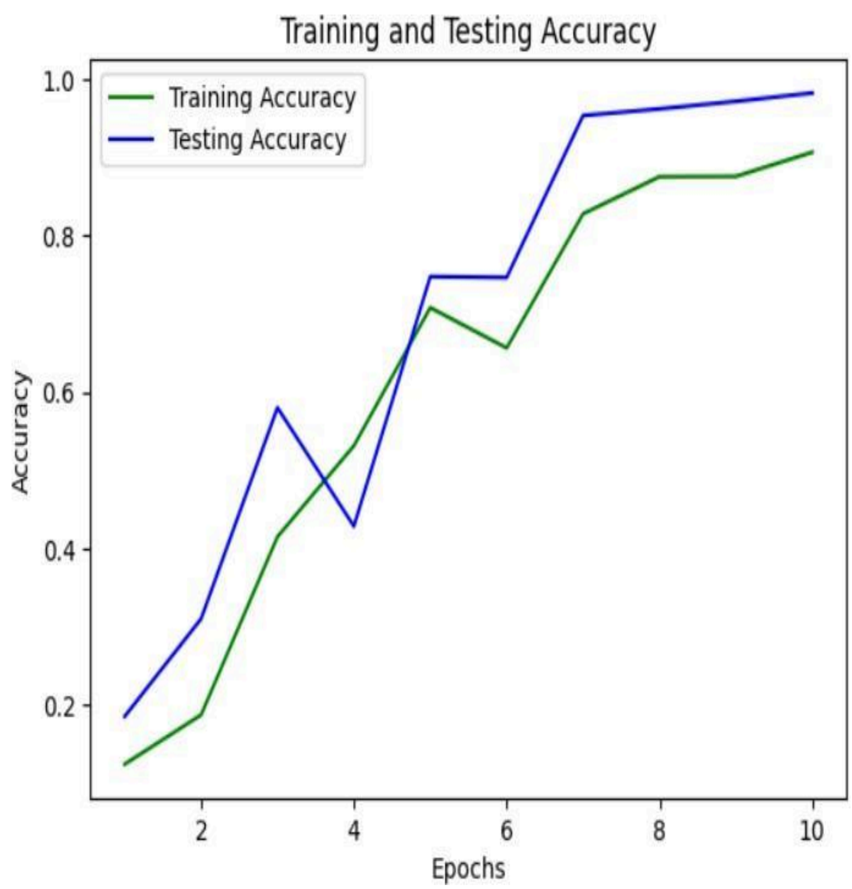

Fig 5.1.4: Training and Testing Accuracy Graph

Training and Testing Loss Graph:

The proposed model is evaluated and the testing and training loss graph is obtained.The training loss typically starts high and gradually decreases as the model learns the underlying patterns in the training data. An ideal graph will show a steady decline in training loss, indicating effective learning.The training and testing loss rate of the model is attached in the below figure 5.1.5

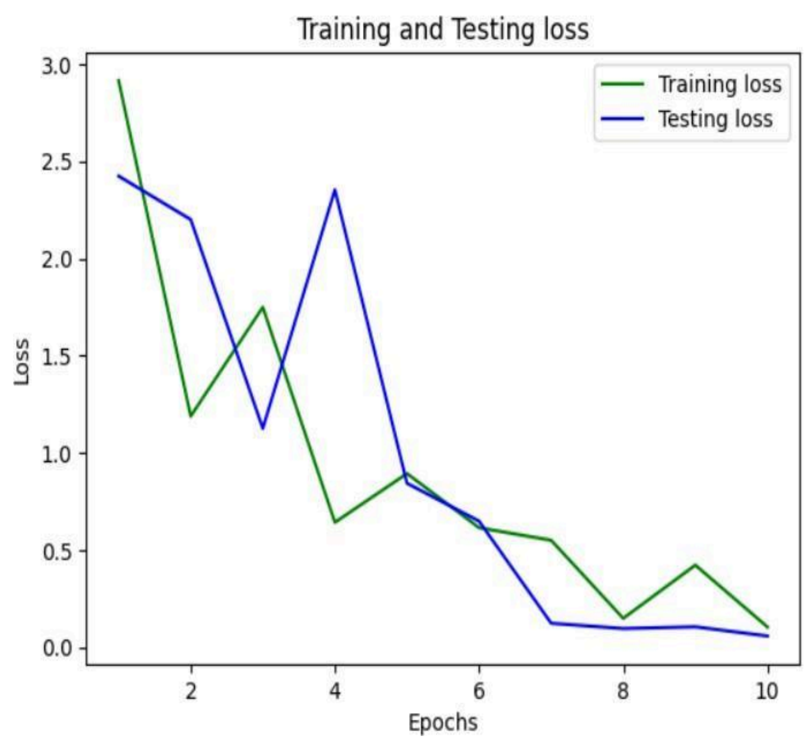

Fig 5.1.5: Training and Testing Loss Graph

5.2 RESULT

The implementation of a Medicinal Plants Identification by Image Processing Using Deep Learning Techniques and Implementing Supply Chain Integrity utilizing CNN Algorithm represents a remarkable journey by achieving 97% accuracy in identifying medicinal plants.The created system, which employs advanced image processing techniques and deep learning algorithms, has extraordinary capability in properly classifying plant species based on visual features derived from photos. Through thorough training on vast datasets of annotated plant photos, the deep learning model has learned to recognize important botanical traits and distinguish between several medicinal plant species with great precision and reliability.

The initiative effectively incorporates supply chain integrity methods, such as blockchain technology, to assure transparency and authenticity throughout the herbal supply chain. This allows stakeholders to trace and verify the authenticity of medicinal plant products from cultivation to consumption, fostering confidence and accountability among growers, processors, distributors, and end users. Overall, the project's excellent accuracy in medicinal plant identification, combined with its strong supply chain integrity measures, marks an important milestone in the herbal business. By delivering dependable and efficient quality assurance and traceability solutions, the project helps to promote consumer health, encourage sustainable herbal medical practices, and reduce fraudulent activity in the herbal supply chain.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The proposed model is an important step forward in the fields of herbal medicine and supply chain management. The proposed idea effectively addressed significant difficulties in medicinal plant identification, authenticity verification, and supply chain transparency by combining cutting-edge technologies such as image processing, deep learning, and blockchain.The created approach has exhibited extraordinary accuracy, reaching a 97% identification rate for medicinal plants using visual characteristics retrieved from photos.The initiative, with its novel methodology and demonstrable outcomes, lays the groundwork for future improvements in herbal medicine research, production, and management, with potential applications reaching beyond the pharmaceutical industry to numerous other businesses.

6.2 FUTURE ENHANCEMENT

Integration with IoT Devices: Connect the identification system to Internet of Things (IoT) devices, such as smart cameras or sensors, deployed throughout the supply chain.

Accessibility and Outreach: Create user-friendly mobile apps or web platforms that allow customers to check the authenticity of medicinal plant items by scanning QR codes or submitting photographs.

APPENDIX

main_app.py:

```
# Library imports
import numpy as np
import streamlit as st
import cv2
from keras.models import load_model
import tensorflow as tf

# Loading the Model
model = load_model('medicinal_plants_cnn.h5')

# Name of Classes
CLASS_NAMES = ('Abelmoschus moschatus medik(Ambrette )', 'Aloe vera (L.) Burm.F(Aloe Vera)', 'Hibiscus rosasinensis(Red Hibiscus)', 'Kaempferia Galanga(Aromatic ginger)', 'Kalanchoe Pinnata (Lam.) Pers(Miracle leaf)', 'Lasia Spinosa (L.) Thwaites(Lesia)', 'Lawsonia inermis L.(Henna)', 'Leucas aspera Link(Thumba)', 'Mentha arvensis L(Corn Mint)', 'Mesua ferrea L.(Nagakesar)', 'Mimusops elengi L.(Spanish cherry)', 'Nyctanthes arbor-Tristis L.(Night Blooming Jasmine)', 'Psidium guajava L.(Guava Seed)', 'Rauvolfia serpentina Benth. Ex Kurz(Serpentine root)', 'Rotheca serrata (L.) Steane & Mabb.(Clerodendrum, Bharangi)', 'Vanilla planifolia(Flat-leaved vanilla)', 'Vitex negundo L.(Chinese Chaste Tree)', 'Zanthoxylum nitidum DC.(Shiny-leaf prickly-ash)', 'Zingiber officinale Rosc.(Ginger rhizome)', 'Ziziphus Jujuba Mill.(Jujube)')
```

```
# Setting Title of App
st.title("Plant Detection")
st.markdown("Upload an image of the plant leaf")

# Uploading the dog image
plant_image = st.file_uploader("Choose an image...", type = "jpg")
submit = st.button('PREDICT PLANT')

# On predict button click
if submit:
    if plant_image is not None:
        # Convert the file to an opencv image.
        file_bytes = np.asarray (bytearray(plant_image.read()), dtype = np.uint8)
        opencv_image = cv2.imdecode(file_bytes, 1)

        # Displaying the image
        st.image(opencv_image, channels="BGR")
        st.write(opencv_image.shape)

        # Resizing the image
        opencv_image = cv2.resize(opencv_image, (150, 150))

        # Convert image to 4 Dimension
        opencv_image.shape = (1, 150, 150, 3)
```

```
    #Make Prediction
    Y_pred = model.predict(opencv_image)
    result = CLASS_NAMES[np.argmax(Y_pred)]
    st.title(str("This medicinal plant is " +  result))
```

medicinal_plants.py:

```
import pandas as pd
import numpy as np
import os
import matplotlib as plt
from sklearn.datasets import load_files

#The path of our data on drive
data_dir =  r'C:\Users\vinot\My ML Projects\Medicinal Plants Classifcation\dataset1'

#Loading our Data
data = load_files(data_dir)

folders=os.listdir(r"C:\Users\vinot\My ML Projects\Medicinal Plants Classifcation\dataset1")
print(folders)
X = np.array(data['filenames'])
y = np.array(data['target'])
labels = np.array(data['target_names'])
```

```
x_tr=97

x_ts=1

print('Data files - ',X)

print('Target labels - ',y)

print('Number of training files : ', X.shape[0])

print('Number of training targets : ', y.shape[0])


from keras.preprocessing.image import img_to_array, load_img


def convert_img_to_arr(file_path_list):

    arr = []

    #size=64,64

    img_width, img_height = 150,150

    for file_path in file_path_list:

        img = load_img(file_path, target_size = (img_width, img_height))

        img = img_to_array(img)

        arr.append(img)

        #arr.append(cv2.resize(img,size))

    return arr


X = np.array(convert_img_to_arr(X))

print(X.shape)

print('First training item : ',X[0])
```

```
import matplotlib.pyplot as plt


fig = plt.figure(figsize = (16,9))
for i in range(5):
    ax = fig.add_subplot(1,5,i+1,xticks=[],yticks=[])
    ax.imshow((X[i].astype(np.uint8)))
    plt.title(folders[y[i]])


# Let's resize or rescale training data
X = X.astype('float32')/255


# Let's confirm the number of classes :)
no_of_classes = len(np.unique(y))
no_of_classes



from tensorflow.python.keras.utils import np_utils


# let's converts a class vector (integers) to binary class matrix.
y = np_utils.to_categorical(y-1,no_of_classes)
y[0]


from sklearn.model_selection import train_test_split
```

```
# let's splite the data into subsets and explore their shapes !

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
print('The test Data Shape ', X_test.shape[0])
X_test, X_valid, y_test, y_valid = train_test_split(X_test,y_test, test_size = 0.5)
print('The training Data Shape ', X_valid.shape[0])

import keras
from keras.models import Sequential
from keras.layers import Conv2D, MaxPool2D, Dense, Flatten, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ReduceLROnPlateau

model = Sequential()

model.add(Conv2D(filters=64, kernel_size=(3,3), padding='same',
input_shape=X_train.shape[1:], activation='relu', name='Conv2D_1'))
model.add(Conv2D(filters=64, kernel_size=(3,3), activation='relu', name='Conv2D_2'))
model.add(MaxPool2D(pool_size=(2,2), name='Maxpool_1'))
model.add(Dropout(0.5))

model.add(Conv2D(filters=128, kernel_size=(3,3), padding='same', activation='relu',
name='Conv2D_3'))
model.add(Conv2D(filters=128, kernel_size=(3,3), activation='relu', name='Conv2D_4'))
model.add(MaxPool2D(pool_size=(2,2), name='Maxpool_2'))
```

```
model.add(Dropout(0.5))


model.add(Conv2D(filters=256, kernel_size=(3,3), padding='same', activation='relu',
name='Conv2D_5'))

model.add(Conv2D(filters=256, kernel_size=(3,3), activation='relu', name='Conv2D_6'))

model.add(MaxPool2D(pool_size=(2,2), name='Maxpool_3'))

model.add(Dropout(0.5))


model.add(Flatten())

model.add(Dense(units=512, activation='relu', name='Dense_1'))

model.add(Dropout(0.5))

model.add(Dense(units=128, activation='relu', name='Dense_2'))

model.add(Dense(units=128, activation='relu', name='Dense_3'))

model.add(Dense(units=128, activation='relu', name='Dense_4'))


model.add(Dense(units=no_of_classes, activation='softmax', name='Output'))


from keras.optimizers import RMSprop


optimizer = RMSprop(learning_rate=0.001, rho=0.9, epsilon=1e-08, decay=0.0)


model.compile(optimizer, loss='categorical_crossentropy', metrics=['accuracy'])


import time
```

```
from keras.callbacks import ModelCheckpoint, EarlyStopping

# Time to train our model !

epochs = 100

batch_size=128

train_datagen = ImageDataGenerator(

        rotation_range=10,

        zoom_range = 0.1,

        width_shift_range=0.1,

        height_shift_range=0.1,

        horizontal_flip=True)

test_datagen = ImageDataGenerator()

train_generator = train_datagen.flow(

    X_train,y_train,

    batch_size=batch_size)

validation_generator = test_datagen.flow(

    X_valid,y_valid,

    batch_size=batch_size)

checkpointer = ModelCheckpoint(filepath = r"C:\Users\vinot\My ML Projects\Medicinal
Plants Classifcation\

                      mediplant.keras", save_best_only = True, verbose = 1)

learning_rate_reduction=ReduceLROnPlateau(monitor='val_accuracy', patience = 3, verbose
= 1, factor = 0.5, minlr = 0.00001)

start = time.time()


history=model.fit(train_generator,
```

```
                    epochs=epochs,
                    validation_data = validation_generator,
                    verbose=1,
                    steps_per_epoch=len(X_train) // batch_size,
                    #validation_steps=len(X_valid) //batch_size,
                    # callbacks=[checkpointer, learning_rate_reduction]
            )
 end = time.time()
duration = end - start
(eval_loss, eval_accuracy) = model.evaluate(
    X_test, y_test, batch_size=16, verbose=2)
print ('\n This Model took %0.2f seconds (%0.1f minutes) to train for %d epochs'%(duration,
duration/60, epochs) )
print("Accuracy: {:.2f}%".format(eval_accuracy * 100))
print("Loss: {}".format(eval_loss))
print('The train Data Shape ', X_test.shape[1:])
x = np.asarray(X_valid)
images = np.vstack([x])
classes = model.predict(images)
print('Predicted class is :')
print((classes))
# Finding max value from predition list and comaparing original value vs predicted
from sklearn.metrics import confusion_matrix
print("Originally : ", folders[np.argmax(y_valid[11])])
```

```
print("Predicted : ", folders[np.argmax(classes[11])])

print(max(y_pred[11]))


# from sklearn.metrics import classification_report

from sklearn.metrics import confusion_matrix

import seaborn as sns

# Predict the values from the validation dataset

Y_pred = model.predict(X_train)

# Convert predictions classes to one hot vectors

Y_pred_classes = np.argmax(Y_pred,axis = 1)

# Convert validation observations to one hot vectors

Y_true = np.argmax(y_train,axis = 1)

# compute the confusion matrix

confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)

# plot the confusion matrix

f,ax = plt.subplots(figsize=(15,15))

sns.heatmap(confusion_mtx, annot=True, linewidths=0.01,cmap="Greens",linecolor="gray",
fmt= '.1f',ax=ax)

plt.xlabel("Predicted Label")

plt.ylabel("True Label")

plt.title("Confusion Matrix")

plt.show()

import matplotlib.pyplot as plt

acc_train = history.history['accuracy']
```

```
acc_val = history.history['val_accuracy']
epochs = range(1,11)
plt.plot(epochs,acc_train,'g',label='Training Accuracy')
plt.plot(epochs,acc_val,'b',label='Testing Accuracy') # validation accuravy
plt.title('Training and Testing Accuracy')    # validation accuravy
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
import matplotlib.pyplot as plt
loss_train = history.history['loss']
loss_val = history.history['val_loss']
epochs = range(1,11)


model.add(Flatten())
model.add(Dense(units=512, activation='relu', name='Dense_1'))
model.add(Dropout(0.5))
model.add(Dense(units=128, activation='relu', name='Dense_2'))
model.add(Dense(units=128, activation='relu', name='Dense_3'))
model.add(Dense(units=128, activation='relu', name='Dense_4'))
plt.plot(epochs,loss_train,'g',label='Training loss')
plt.plot(epochs,loss_val,'b',label='Testing loss')# validation loss
plt.title('Training and Testing loss')# validation loss
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')

plt.legend()

plt.show()

print('The train Data Shape ', X_test.shape[1:])

x = np.asarray(X_valid)

images = np.vstack([x])

classes = model.predict(images)

print('Predicted class is :')

print((classes))

# Finding max value from predition list and comaparing original value vs predicted

from sklearn.metrics import confusion_matrix

print("Originally : ", folders[np.argmax(y_valid[11])])

print("Predicted : ", folders[np.argmax(classes[11])])

print(max(y_pred[11]))
```

REFERENCES

[1] I. Volkmer, News in the Global Sphere: A Study of CNN and Its Impact on Global Communication. Indiana University Press, 1999.

[2] C. Crossley, Software Supply Chain Security. “O’Reilly Media, Inc.,” 2024.

[3] S. Inam, S. Kanwal, R. Firdous, and F. Hajjej, “Blockchain based medical image encryption using Arnold’s cat map in a cloud environment,” Sci. Rep., vol. 14, no. 1, p. 5678, Mar. 2024.

[4] D. Chhabra, Authenticity and Authentication of Heritage. Routledge, 2021.

[5] Herbal Leaves Classification Based on LeafImage Using CNN Architecture Model VGG16

[6] A new approach to learning and recognizing leaf diseases from individual lesions using convolutional neural networks Lawrence C. Ngugi, Moataz Abdelwahab, Mohammed Abo-Zahhad 2023

[7] Comparison of data preprocessing approaches for applying deep learning to human activity recognition in the context of industry 4.0-X Zheng, M Wang, J Ordieres-Meré - Sensors, 2018

[8] A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting A Kurani, P Doshi,2023

[9] Classification of medicinal plants leaves using deep learning technique: A review H Chanyal, RK Yadav, DKJ Saini - … Journal of Intelligent Systems,2022.

[10] A deep learning based model for the detection of pneumonia from chest X-ray images using VGG-16 neural networks S Sharma, K Guleria - Procedia Computer Science, 2023

[11] Plant disease and pest detection using deep learning-based features M Türkoğlu, D Hanbay Turkish Journal of Electrical- 2019

[12] A review on extreme learning machine J Wang, S Lu, SH Wang, YD Zhang - Multimedia Tools and Applications, 2022

[13] Iris Features Extraction and Recognition based on the Scale Invariant Feature Transform (SIFT) MA Taha, HM Ahmed, SO Husain - Webology, 2022

[14] A five-layer deep convolutional neural network with stochastic pooling for chest CT-based COVID-19 diagnosis.

[15] Confusion matrix-based modularity induction into pretrained CNN-S Ahmad, SU Ansari, U Haider, K Javed… - Multimedia Tools,2022.

[16] "Blockchain Integration for Medicinal Plant Supply Chain Integrity," 2022 P. Zhao and T. Clark

[17] "Mobile Applications for Real-Time Medicinal Plant Identification," 2022 by S. Li and E. Thompson

[18] "Hybrid Machine Learning Models for Enhanced Plant Identification," 2022 by A. Hernandez and R. Kumar

[19] "Transfer Learning Approaches in Medicinal Plant Recognition," 2022 by L. Nguyen and M. Patel

[20] "Automated Medicinal Plant Identification Using Deep Learning," 2022 by J. Smith