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Together : Awareness App and Novel IoT-Enabled Smart- Agriculture System using Deep learning

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ABSTRACT

Climate change has a profound impact on agriculture, as it depends on climate and environmental conditions. The rise in pests and diseases is a significant threat to crop yields, causing global crop production to experience yearly losses of up to 40% [1]. This loss has severe implications, leading to food insecurity and economic hardship worldwide. These, in turn, cost the global economy billions of dollars and pose a significant threat to global food security. Unfortunately, there is a common misconception that individual actions cannot make a huge difference in the fight against climate change. People tend to believe that the available solutions are too complex and inaccessible, leading to a sense of hopelessness. However, we must realize that acting on an individual level is crucial in the battle against this global crisis. Every effort made, no matter how small, has the power to create a ripple effect and inspire others to do the same. This misconception often stems from a lack of access to tools and knowledge that could help them make a meaningful impact. Our project aims to address this issues by developing 2 main outcomes, the first one is an empowering mobile app that provides a tool for users to help them normalize planting around them through our AI-powered smart planting guide, a community platform for raising awareness about climate change and sharing experiences and a pollution reporting feature and the second is a novel smart agriculture system that will help mitigate the effects of climate change on the agriculture sector. The system aims to provide farms and agricultural domains with comprehensive tools that will enable them to reduce the impact of climate change on crop yields and increase productivity. It will provide farms with a range of features and precision agriculture services like intelligent weed detection (common crop weeds), disease detection in rice and crop recommendation system based on soil analysis and IoT that provide insights to the farmers. The proposed novel smart agriculture system offers many services that address the challenges of climate change by decreasing greenhouse gas (GHG) emissions and increasing crop productivity. The system can reduce the presence of weeds within crops, monitor crop diseases to prevent them from spreading, and recommend crops based on environmental conditions such as humidity, temperature, and rainfall rate.

I. INTRODUCTION

Our Earth is dealing with a major issue known as climate change, as it affects our planet in numerous ways. One of the most significant impacts of climate change is on agriculture, where it poses a major threat to crop yields by increasing the spread of pests and diseases, resulting in annual losses of up to 40% of crop production worldwide. This, in turn, costs the global economy billions of dollars and poses a significant threat to global food security. Weeds and crop diseases are the most common affecting issues that cause crop loss. Today losses caused by weeds and insects can reach 40% of total crop yields each year and this percentage is expected to increase significantly in the coming years [2].

In an attempt to mitigate crop losses resulting from weeds and crop diseases, farmers are increasingly turning to chemical inputs such as fertilizers and pesticides. However, the uncontrolled and excessive use of these products poses a significant risk to both human health and the environment. In fact, a study by Costello et al. [3] demonstrated that living within 500 meters of agricultural land where pesticides are applied can increase the risk of Parkinson's disease by up to 75%.

To address this issue, farmers are now exploring a more precise and smart approach to farming called precision agriculture. This new approach aims to allocate the right doses of inputs such as fertilizers, herbicides, seed, and fuel, at the right time and place, using advanced technologies such as sensors, and machine learning algorithms. By adopting precision agriculture practices, farmers can minimize the use of chemical inputs, reduce the risk of environmental pollution, and optimize crop yields.

Moreover, precision agriculture can help farmers save on costs associated with overuse or misuse of inputs, and also reduce the need for manual labor. Weed detection is a critical task in modern agriculture as it poses a significant threat to crop yields by competing with the main crop, particularly in the early stages of growth. In recent years, there has been an increasing demand for efficient and accurate weed detection techniques to reduce crop losses and optimize crop management practices.

To address this need, we have developed a novel smart agriculture system that employs advanced deep learning algorithms to provide three main features, which are, intelligent weed detection system, intelligent paddy diseases detection system and crop recommendation and support system

The first one is the Intelligent weed detection system to identify weeds in crop fields in multiple growth stages. The system is capable of identifying up to 15 different types of weeds, which are commonly found in agricultural fields. This system has the potential to significantly improve weed management practices, by detecting and controlling the spread of weeds at an early stage, thereby reducing the overall impact on crop yields. The deep learning models used in the system are based on **ResNet50** and **EfficientNetB2** pre-trained models that can automatically extract high-level features from images of the crop fields.

The other factor that can drastically impair crop production is the pathogens such as fungi and bacteria can lead to **crop diseases**. Because the illness is difficult to control on a broad scale, crop field monitoring is one of the most effective methods of control. It allows for early detection of the disease and the implementation of preventative measures. Our research has led us to focus on rice crops as they are a crucial source of food for many countries, and disease can cause significant economic losses

Agro-meteorological factors can cause diseases in rice, and accurate diagnosis and treatment are essential for crop protection. Disease severity estimation based on digital image analysis has proven to be an effective strategy. However, excessive usage of chemical pesticides can increase the toxic level in agricultural products and production costs. Therefore, it is necessary to use pesticides cautiously by identifying the severity of the disease and targeting the affected areas. In order to tackle this issue, we are proposing an **Intelligent paddy diseases detection system** as a second feature provided by our novel smart agriculture system , we developed a fine-tuned transfer learning model to identify 15 different paddy diseases. The model uses the **ResNet34** pre-trained model to classify the diseases.

The agricultural sector plays a significant role in a country's economy. Choosing the right crop based on factors such as soil quality, weather, water availability, seed availability, and crop cultivation knowledge is crucial. The term precision agriculture has been used to describe the incorporation of various technologies into traditional farming practices, to improve agricultural productivity and sustainability [4]. Modern technologies such as the Internet of Things (IoT) paves the foundation of precision agriculture that enables the minimization of human labor and cost as well as improving agricultural productivity. IoT generates large volumes of data which can be used for practices such as crop monitoring or disease detection. The analysis and interpretation of this data enables the understanding of relationships between various agricultural factors such as soil characteristics and climatic variables.

The support system's ultimate goal is to provide continuous support to farmers, giving them regular updates about their crops and fields, enabling them to make better decisions. To improve crop prediction and production, it's essential to consider various factors such as soil properties, weather conditions, water availability, temperature, sunlight, wind, and pollution levels. By using sensors to collect area-wise soil properties for nitrogen, phosphorus, potassium, pH value, temperature, moisture, and rainfall levels, farmers can determine the ideal crops to grow in a particular field.

Therefore, we are proposing a new IoT-enabled soil analysis and crop recommendation support system **IoT- SACRSS** that will assist farmers in selecting the most suitable crops for each season based on soil nutrients and climate variables and also providing precision agriculture with insights to help them save their crops and increase productivity. The system relies on a **Random Forest classifier model** that predicts the most suitable crops to grow based on temperature, soil pH, NPK values, humidity, and rainfall rate and with fuzzy logic and knowledgebase data the system returns the top 3 crops that will give the maximum productivity and minimum CO_2 emissions from a 22 crop overall. The support system provides data-driven recommendations for achieving optimal nutrient quantities to improve crop yield. It recommends a customized mix of soil enhancers, such as urea and compost.

The global community is facing the consequences of climate change especially in developing countries, and it is essential to take action to mitigate its effects. As part of this effort, we have developed an empowering app that provides users with a comprehensive tool to help them make a positive impact on the environment. The main feature is the AI-powered smart planting guide that helps individuals to normalize planting around them and make planting easier. In order to achieve this, we have developed two deep learning models using transfer learning to identify the plants' type.

Transfer Learning [5] is a technique for reusing a model that has already been trained on a huge dataset. It assists in the accurate detection of plant types. The smart planting guide identifies the plant type from either the leaves or the flowers of the plant. The flower classification model is based on the ResNet50 lightning pre-trained model architecture to perform classification on 16 different types of flowers. And for the leave's classification model, it relies on a Linear Discriminant Analysis (LDA) that classifies different types of plants using leaves. We have developed a classification algorithm classifying 99 plant types.

Our app also includes a community platform for raising awareness about climate change and sharing experiences. Additionally, our app has pollution reporting feature that allows the users to report any pollution activity especially the rice straws burning. Through these features, our app offers a practical solution for individuals to contribute towards environmental conservation. Overall, our app aims to empower individuals to make a significant impact on the environment and help them take steps towards a more sustainable future.

1.1 Objectives

The main objectives of this project are to develop these two outcomes, the empowering mobile app, and the smart agriculture system, to address the challenges faced by the agriculture sector due to climate change. The first objective is to develop an empowering mobile app that will provide a tool for users to help them normalize planting around them through our AI-powered smart planting guide, a community platform for raising awareness about climate change and sharing experiences, a pollution reporting feature. The second objective is to develop a novel smart agriculture system that will help mitigate the effects of climate change on the agriculture sector. The system aims to provide farms and agricultural domains with comprehensive tools that will enable them to reduce the impact of climate change on crop yields and increase productivity. The system will provide farms with a range of features and precision agriculture services like intelligent weed detection (common weeds), disease detection and crop recommendation system based on soil analysis and IoT that provide insights to the farmers.

II. LITERATURE SURVEY

2.1 Methodology:

A systematic search was conducted using several online databases, including ResearchGate, IEEE Xplore, ACM Digital Library, and ScienceDirect. Keywords such as "climate change," "plant classification," "precision agriculture," "deep learning," "crop recommendations," "weed detection," "disease detection," "flower classification " and "smart farming" were used to identify relevant articles. Only peer-reviewed articles published in the last five years were included in this survey.

2.2 Literature Review:

In this section, we conducted a literature survey on climate change, agriculture, deep learning, and related tools and techniques. We reviewed several research papers, articles, and online resources to gain a better understanding of the subject matter. We also studied existing applications and systems that address climate change and agriculture sustainability. Researchers have attempted several methods to classify and diagnose plant diseases and extract their features. Deep learning alongside image processing and traditional machine learning techniques have been extensively used in the agricultural field. This section concentrates on some of the previous work that uses deep learning techniques to classify rice crops diseases, weed classification, leaves classification, flowers classification from digital images and crop recommendation systems using soil analysis.

In recent times, Deep Learning and in particular the use of Convolutional Neural Networks (CNNs) has proven well suited for addressing computer vision problems of which plant classification can be considered to be one. Deep learning eliminates the need for domain expertise and hard-core feature extraction that only expert botanists can provide. One of the approaches used for weeds detection is machine learning. Bakhshipour and Jafari [6] evaluated weed detection with support vector machine (SVM) and ANN in four species of common weeds in sugar beet fields using shape features.

In [7], a semi-automatic Object Based Image Analysis (OBIA) procedure has been developed with Random Forests (RF) combined with feature selection techniques to classify soil, weeds, and maize. With all these articles, we can notice that the selected features change in general from one type of culture to another or from one type of data to another. Milioto et al. [8] provided accurate weed classification in real sugar beet fields with mobile agricultural robots. Bah et al. [9] applied AlexNet for weed detection in different crop fields such as beet, spinach, and bean in UAV imagery.

In a recent study, Di Cicco et al. [10] suggested the use of synthetic training datasets. However, this technique requires precise modeling in terms of texture, 3D models and light conditions. Currently, most methods used for unsupervised data collection detect crop rows first, then label plants within the rows as crops and those between rows as weeds (inter-row weed) [11]. These methods strongly depend on the presence of weeds in the inter-row. Therefore, labeled data will be very unbalanced in cases where the field has fewer weeds between crop rows. This can reduce the efficiency of the trained models and promote overfitting. Though many open-source agriculture datasets have been available in recent years, the quality and amount of data do not meet the requirements of researchers [12, 13].

In addition, models trained with such data fail to generalize and are not robust enough to be used in diverse practical environments [14]. One way to overcome these difficulties is by adopting image geometric- and intensity-based data augmentation [15, 16]. In addition, when CNNs are employed for machine vision tasks, transfer learning is preferred [15], where a pre-trained deep-learning model is fine-tuned with an available dataset for a particular task [17]. This approach has seen a lot of utilization for in-field weed identification [18-20]. For instance, Espejo-Garcia et al. developed a solution based on feature extraction from deep layers of various transfer-learned CNN models for automated crop and weed identification [18].

However, such traditional image augmentation techniques and transfer learning provide highly correlated images and only little additional information to the deep-learning model. This not only reduces the ability of the model to generalize but leads to over-fitting problems. Several researchers have proposed an automated identification system for rice disease detection. In [21], rice disease detection was accomplished by considering the area of the diseased leaf using image processing and a model was developed using the Naive Bayes Classifier. This classifier could identify three types of diseases of paddy plants with a prediction accuracy of 89%. In [22], CNN and Multilayer Perceptron (MLP) models were proposed to achieve 81.03% and 91.25% accuracy.

Author Chen et al. [23] used deep learning techniques to improve image processing and classification. They combined Dense Net and Inception modules and achieved high accuracy on a public dataset, with an average of 94.07% or higher. Their model also achieved an average accuracy of 98.63% for classifying rice disease images. Lei Feng et al. [24] employed hyperspectral imaging(HSI) to detect paddy leaf diseases and developed a CNN architecture as a classification model using deep transfer learning techniques. They found fine-tuning was the most efficient solution, achieving 88% accuracy.

The field of smart farming heavily relies on the integration of machine learning and IoT technologies, but implementing these technologies comes with challenges. However, handling the hardware units and sensors can be challenging due to environmental factors. Soil fertility is critical to maintaining crop production levels, but the nutrient levels of soil decrease over time due to cultivation. One method to improve soil fertility is by optimally increasing it using sensor technology, which can improve soil quality, food safety, and crop profitability. One author suggested a model that implements sensors and machine learning in every stage of precision farming, including water management, crop selection, nutrient management, crop health management, yield management, and post-harvest management, to increase agricultural production levels. Different sensors can measure humidity, water level, soil moisture and pH value [25].

Smartphone applications are useful for integrating data aggregation, processing speed, and IoT ideals. These applications can collect information from weather stations and remote sensors for detailed analysis, enabling farmers to make decisions on weeding, watering, seeding, and fertilizing. One such application gathers data on soil tests, enabling machine learning algorithms to recommend suitable crops based on the results.

The excessive use of chemical fertilizers imbalances the availability of soil nutrients, which are collected, classified, and can be analyzed using an extreme machine learning decision system. Hence, we should avoid a deficiency in NPK fertilizer in plants, as it might lead to bad results. Excess usage of fertilizer imbalances ecosystems. Precision agriculture assists with the appropriate usage of NPK fertilizer through IoT, WSN, and machine learning techniques [26].

Shubham Prabhu, et.al. [27] has proposed a paper in which they put forward the soil analysis and crop prediction model. The main aim of the paper is to create a prediction engine that will be for the most suitable crop for a particular soil. As an initial step, authors have focused on predicting the accurate crop yield to the user by just analyzing the soil fertility as well as rainfall in the region entered by the user as an input. Basically, author considered five soil samples from different regions and then analysis is done based on temperature, moisture and humidity which is carried out at a regular interval of 24 hours and the data is uploaded, displayed, and updated at an interval of 2 hours. All the data that is analyzed is continuously monitored, displayed, and uploaded on the IoT cloud. They have basically used three algorithms Naïve Bayes, Logistics and C4.5 [28] in which has given accuracy of 85% .

As machine learning technology advances, increasingly sophisticated models have been proposed for automatic plant identification. With the widespread use of smartphones and the emergence of mobile apps like PlantNet [29], millions of plant photos have been collected. Mobile-based automatic plant identification is essential for real-world applications such as social-based ecological surveillance [30], invasive exotic plant monitoring [31], ecological science popularization, and more. Improving the performance of mobile-based plant identification models has become a priority for scholars and engineers.

In recent years, many efforts have been made to extract local characteristics of leaves, flowers, or fruits. Most researchers use variations in leaf characteristics as a comparative tool for studying plants, and some leaf datasets, including the Swedish leaf dataset, Flavia dataset, and ICL dataset, are considered standard benchmarks. In [32], Soderkvist extracted shape characteristics and moment features of leaves and analyzed 15 different Swedish tree classes using backpropagation for the feed-forward neural network. Nilsback and Zisserman proposed a method of bag of visual word to describe the color, shape, texture features, and other characteristics [33]. In [34], Zhanget al. combined Harr features with SIFT features of flower image, coding them with nonnegative sparse coding method and classifying them by k-nearest neighbor method.

After so many years of continued exploration into plant recognition technology, the dedicated mobile applications such as LeafSnap [35], Pl@ntNet [29], can be conveniently used for identifying plants. In [36] the author has used a deep residual network that uses a residual map to identify the pest, including improved computational frameworks, specifically Graphical Processing Units (GPU) embedded processors. The author used DL to identify plant diseases. A deep convolutional neural network was used in this research. CNN, RNN, and GAN are the most common Deep Learning algorithms.

2.3 Findings:

The literature survey found that creating awareness about climate change is a complex issue, and traditional methods have not delivered fast enough results. Mobile applications have shown promise in promoting awareness and motivating individuals to take small actions that contribute to reducing climate change. AI and IoT technologies can be used to provide intelligent weed and disease detection systems, climate-friendly crop recommendations, and planting smart guides. The proposed smart farming system offers many services that address the challenges of climate change. The system can reduce the presence of weeds within crops, monitor crop diseases to prevent them from spreading, and recommend crops based on environmental conditions such as humidity, temperature, and rainfall rate. Deep learning models have shown promise in detecting weeds and diseases in crops and using them can significantly reduce the need for pesticides and herbicides.

III. PROBLEM SPECIFICATION

Climate change has been identified as a significant threat to agriculture, resulting in annual crop production losses of up to 40%. The rise in pests and diseases due to climate change has led to severe implications, such as food insecurity, economic hardship, and a threat to global food security. Unfortunately, the general public often believes that individual actions cannot make a substantial difference in the fight against climate change, leading to a sense of hopelessness. This misconception may stem from a lack of access to tools and knowledge that could help people make a meaningful impact. Therefore, there is a need to develop an empowering mobile app and a novel smart agriculture system that will provide comprehensive tools to address the challenges of climate change in agriculture. The mobile app will feature an AI-powered smart planting guide that helps users to normalize planting around them, a community platform for raising awareness about climate change, and a pollution reporting feature. The smart agriculture system will provide farmers with a range of features and precision agriculture services such as intelligent weed detection, disease detection in rice, and a crop recommendation system based on soil analysis.

The problem specification will focus on the development of the two outcomes, the mobile app, and the smart agriculture system. The primary aim is to provide comprehensive tools to enable farmers and individuals to reduce the impact of climate change on agriculture and increase productivity. The challenges that will be addressed include increasing crop productivity, reducing the presence of weeds within crops, and preventing the spread of crop diseases

IV. IMPLEMENTATION

This section describes some main concepts and methods used in the proposed models and applications. We have implemented the whole project through **3** main phases.

Phase I : Data Acquisition

A collection of six datasets that are involved which are: flower classification, leaf classification, cotton weeds, crop recommendation data, paddy diseases and weed seedlings, to satisfy model's training needs.

1- Flowers Dataset [37]

The flower classification dataset is a collection of images of flowers from 16 different species. The dataset contains a total of 15740 images, with between 800 to 1027 images per species. Each image is labeled with the species it belongs to, making it a supervised learning problem for classification.

2- Leaves Dataset [38]

The Leaf Classification dataset consists approximately 1,584 images of leaf specimens (16 samples each of 99 species) which have been converted to binary black leaves against white backgrounds. Three sets of features are also provided per image: a shape contiguous descriptor, an interior texture histogram, and a fine-scale margin histogram. For each feature, a 64-attribute vector is given per leaf sample.

3- Paddy Diseases Dataset [39]

The Paddy Doctor Dataset provides a training dataset of 10,407 (75%) labeled paddy leaf images across ten classes (nine diseases and normal leaf). We also provide additional metadata for each image, such as the paddy variety and age. Our task is to develop an accurate disease classification model using the training dataset and then classify each sample in the test dataset of 3,469 (25%) paddy leaf images into one of the nine diseases or normal leaf.

4- Seedlings Dataset [40]

The plant seedling classification dataset contains a collection of images of plant seedlings from 12 different species. The 12 different species divided as weeds and crops, 8 seedlings correspond to wild weeds like: loose silky-bent, common chickweed, scentless mayweed, small-flowered cranesbill, fat hen, charlock, cleavers, black-grass, and shepherd's purse and 4 seedlings that belong to common agriculture crops like sugar beet, maize, and common wheat at various stages of growth. The dataset contains a total of 5,539 images in the training set and 7,303 images in the test set, with each image labeled with the species it belongs to.

5- Crop Recommendation Dataset [41]

The Crop Recommendation dataset is a collection of data related to crop farming. The dataset includes information on different parameters such as soil content, temperature, humidity, and rainfall, which can be used to make informed decisions about farming strategy. The goal is to build a predictive model that can recommend the most suitable crops to grow in a particular farm based on these parameters. The dataset was constructed by aggregating datasets of rainfall, climate, and fertilizer data from India.

6- Cotton Weeds Dataset [19]

The dataset CottonWeedID15 consists of 5187 RGB images of 15 weeds that are common in cotton fields in the southern U.S. states. The images were manually labeled by weed scientists and trained individuals. The images are in JPEG format and have a resolution of 256 x 256 pixels.

Phase II : Preprocessing Data & Training the Models

After choosing the suitable dataset for each feature, the authors moved forward to build and train machine and deep learning models, starting with the **IoT-Enabled Smart Agriculture System :**

To develop the **Intelligent weed detection system**, we have started to prepare our data. We had to prepare two datasets, the Cotton Weeds dataset, which consists of 15 weeds and the Plant Seedlings Dataset, consists of plant seedlings from 12 different species divided as 8 seedlings for weeds and 4 seedlings that belong to common agriculture at various stages of growth.

- **Data Preprocessing**

For the Cotton Weeds dataset, we have used data augmentation, which is a technique used in machine learning and computer vision to increase the diversity of a training dataset. This is achieved by applying various transformations to the images or data samples, such as rotation, flipping, cropping, and color changes, in order to create new variations of the original data. These augmented samples can then be used to train machine learning models, improving their ability to generalize to new, unseen data.

The authors have used a custom augmentation function (see **Fig**. 3), that applies a series of data augmentations to each image in the dataset. The augmentations are defined using the transforms module from PyTorch, and include random rotations, flips, and affine transformations, as well as random cropping with size (224, 224) and color jittering. The RandomApply function is also used to apply certain augmentations with a probability p, allowing for additional randomness in the dataset.

```
transforms.RandomApply([transforms.RandomCrop(size=(224, 224), padding=20)], p=0.3),
transforms.RandomApply([transforms.GaussianBlur(kernel_size=3, sigma=(0.1, 2.0))], p=0.2),
transforms.RandomApply([transforms.RandomPerspective(distortion_scale=0.2)], p=0.2),
```

Fig 1. Code snippet shows the RandomApply function.

For the Plant Seedlings dataset, we have used data augmentation, with, such as horizontal flipping, shearing, scaling, translation, rotation, and brightness shift, to enhance the training process. These augmentations aimed to diversify the training data, improve the model's ability to handle variations in object orientation, shape, position, lighting conditions, and enhance its generalization. The ImageDataGenerator from TensorFlow was employed for data loading and augmentation operations, resulting in improved performance and robustness of the model.

- **Building & Training the Models**

After preparing the data of both datasets, the authors have developed two transfer learning classifiers, a fine-tuned ResNet50 deep learning model for the task of classifying cotton weeds into 15 categories and EfficientNetB2 deep learning model for classifying the plant seedlings.

- **ResNet50**

ResNet50 is a powerful convolutional neural network architecture that has been widely used in computer vision tasks due to its ability to achieve state-of-the-art performance on a variety of datasets. It uses the Residual Connections approach, which avoids "gradient vanishing" and speeds up the training. ResNet50 builds upon ResNet34 by utilizing a deeper network architecture to achieve higher accuracy without encountering the vanishing gradient problem.

The ResNet50 architecture consists of 50 layers that function hierarchically (see **Table** 1), with the initial layers extracting low-level features and the deeper layers learning more complex, high-level features. Feature extraction is achieved using convolutional layers, batch normalization, and the Rectified Linear Unit activation function. The first layer is a convolutional layer with a 7x7 kernel size and a stride of 2, followed by a max-pooling layer with a 3x3 kernel size and a stride of 2 **(**see **Fig.** 2**)**.

Table 1. Resnet50 layers.

Layer name	Output Size	18-Layer	34-Layer	50-Layer	101-Layer	152-Layer
Conv1	112X112	7x7, 64, stride 2				
Conv2_X	56X56	3x3 Max pool, stride 2				
		[3x3,64 3x3,64] X2	[3x3,64 3x3,64] X3	[1x1,64 3x3,64 1x1,256] X3	[1x1,64 3x3,64 1x1,256] X3	[1x1,64 3x3,64 1x1,256] X3
Conv3_X	28x28	[3x3,128 3x3,128] X2	[3x3,128 3x3,128] X4	[1x1,128 3x3,128 1x1,512] X4	[1x1,128 3x3,128 1x1,512] X4	[1x1,128 3x3,128 1x1,512] X8
Conv4_X	14x14	[3x3,256 3x3,256] X2	[3x3,256 3x3,256] X6	[1x1,256 3x3,256 1x1,1024] X6	[1x1,256 3x3,256 1x1,1024] X23	[1x1,256 3x3,256 1x1,1024] X3
Conv5_X	7x7	[3x3,512 3x3,512] X2	[3x3,512 3x3,512] X3	[1x1,512 3x3,512 1x1,2048] X3	[1x1,512 3x3,512 1x1,2048] X3	[1x1,512 3x3,512 1x1,2048] X3
	1X1		Average pool, 1000-d fc, softmax			

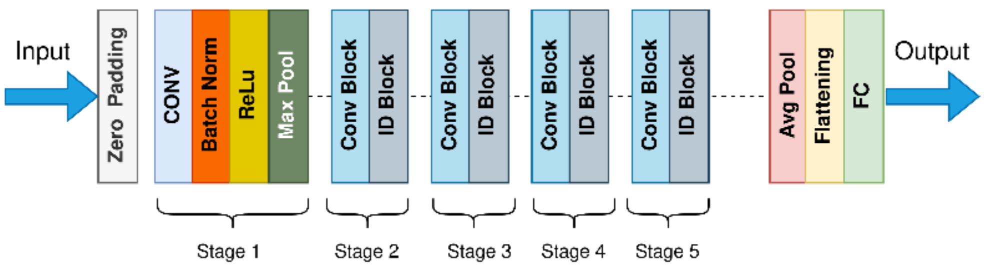


Fig 2. Resnet50 architecture (Wikimedia Commons)

For the training phase, a PyTorch Dataset object has been used, which can be passed to a Data Loader for efficient loading and batching of the data. During the classification stage, the ResNet50 network uses the extracted features to classify the input image into one of 15 categories, to identify the weeds. The features are passed through fully connected layers to produce a probability distribution over the feasible categories, with the category having the highest probability being designated as the predicted class of the image. Our implementation of the ResNet50 model was built using the PyTorch Lightning framework, which provides a high-level interface for training and evaluating deep learning models. The model was initialized with weights pre-trained on the large-scale ImageNet dataset, which contains over 1 million labeled images across 1,000 categories. This pre-training allowed the model to learn a set of general features that could be fine-tuned for the specific task of weed classification.

The ResNet50 model consists of multiple layers of convolutional and pooling operations, followed by a fully connected layer that produces the final predictions. We replaced the original fully connected layer with a new one consisting of two linear layers and a dropout layer in between, with the final output layer having the same number of neurons as the number of classes in our dataset (i.e., fifteen). We used the cross-entropy loss function to calculate the difference between the predicted and actual labels during training. We used the Adam optimizer with a learning rate of 3e-4 and a StepLR learning rate scheduler, which reduces the learning rate by a factor of 0.1 every two epochs (see **Fig** 3). We used a stratified k-fold cross-validation approach with 4 folds to evaluate the model's performance on our dataset.

K-fold cross-validation is a technique that helps in assessing the performance of a model by dividing the dataset into K subsets or folds of approximately equal size. The K-fold cross-validation method involves splitting the data into K parts, where K-1 parts are used for training the model, and the remaining one part is used for testing the model's performance. This process is repeated K times, with each subset used as the testing data once. The results are then averaged across the K experiments to get a final estimate of the model's performance (see **Fig** 4).

The K-fold cross-validation is that it helps in providing a more accurate estimate of a model's performance. By using multiple splits of the data, we can get a better sense of how well our model generalizes to new data. K-fold cross-validation is used to evaluate the ResNet50Model. The dataset is split into 4 folds using the Stratified Fold function from scikit-learn. For each fold, a new instance of the ResNet50Model is created, and the model is trained on the training subset and evaluated on the validation subset using the PyTorch Lightning Trainer.

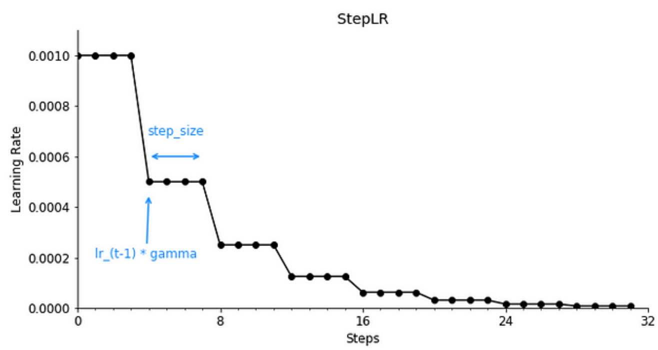


Fig 3. Step Learning Rate scheduler (Leonie Monigatti, 2022)

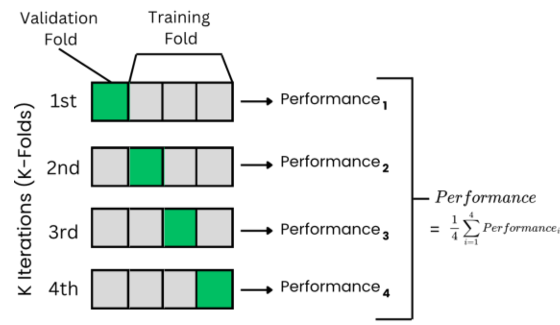


Fig 4. K-fold cross-validation

During training, we monitored the loss and accuracy metrics on both the training and validation datasets and used early stopping with a patience of two epochs to prevent overfitting. We also used the PyTorch Lightning metric module to calculate the accuracy of the test dataset after training was complete.

- **EfficientNetB2**

It is a convolutional neural network architecture (see **Fig**. 5) with a scaling method that uniformly scales depth, width, and resolution using a compound coefficient. This scaling approach enables efficient utilization of computational resources by uniformly adjusting network depth, width, and image size.

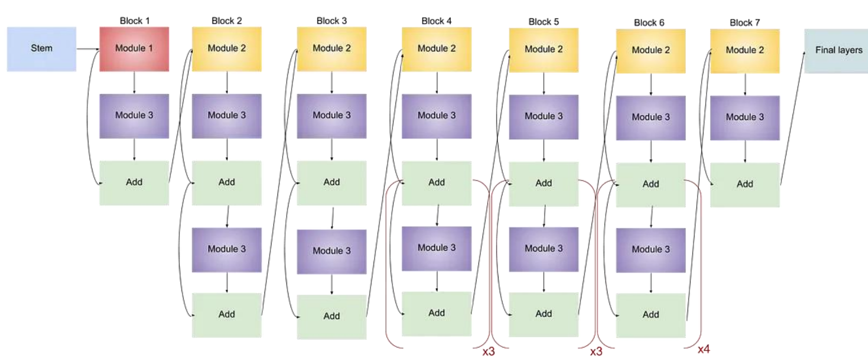


Fig 5. EffiecientNetB2 Model architecture (Agarwal, 2020)

The images were organized into a directory structure where each species had its own subdirectory containing the images. The dataset was split into a training set (80% of the images) and a validation set (20% of the images). We used Keras' ImageDataGenerator to apply data augmentation techniques such as rotation, shifting, shearing, zooming, and flipping to the training set images. This augmented data was used to train the model and improve its generalization performance. The model building process focused on implementing an efficient model to classify the weeds and crops seedlings with high accuracy.

The model's top layers were excluded to allow for customization. A global average pooling layer was added to obtain a fixed-length representation of the feature maps. To construct the predictor layers, a series of fully connected (Dense) layers were added, with ReLU activation functions for non-linearity. Dropout regularization was incorporated to prevent overfitting. The final layer consisted of a Dense layer with a softmax activation function, producing probabilities for each of the 12 target classes.

The model was compiled using the Adam optimizer, Categorical Crossentropy loss function, and Categorical Accuracy as the evaluation metric. The model was trained using the provided training and validation data generators with a batch size of 32 for a total of 40 epochs. These training settings aimed to optimize model performance while preventing overfitting. The model was evaluated after each epoch using the validation set to monitor its performance and to prevent overfitting. The performance of the model was evaluated using accuracy and categorical cross-entropy loss metrics.

Moving to the **Paddy diseases detection system**, we have started to prepare the dataset, The Paddy Doctor dataset contains 16,225 labeled paddy leaf images across 10 classes (9 different paddy diseases and healthy leaves). Our main objective is to develop a deep learning-based model to classify the given paddy leaf images accurately. Therefore, we are proposing a highly effective deep learning model based on the fine-tuned Residual Neural Network (**ResNet34**) architecture.

- **Data Preprocessing**

We started with a preprocessing pipeline that was designed to prepare image data for training and evaluation. The pipeline encompassed several key steps to ensure optimal data representation and facilitate efficient model learning. The dataset was split into separate training and validation sets, which allocated 90% of the data for training and 10% for validation. Furthermore, random shuffling of the was performed to eliminate any potential biases caused by the original order of the data. This randomization step enhances the generalization capabilities of the model by exposing it to a diverse and unbiased distribution of images during training. The preprocessing pipeline also incorporated a series of transformations to standardize and enhance the images. These transformations, encapsulated within the `transform` variable, included center cropping the images to a size of 446 pixels, resizing them to a uniform size of (256, 256) pixels, converting them to tensors and normalizing their pixel values. The normalization step employed specific mean and standard deviation values to align the image data with a standard distribution, facilitating more effective training and convergence of the model.(see **Fig**. 6)

Fig 6. Sample of the augmented images

- **Building & Training the Models**

To train the model, we used the cross-entropy loss function, which is commonly used for multi-class classification problems. The Adam optimizer was employed to optimize the model parameters, with a learning rate of 1e-4. During training, we ran the model for 10 epochs and monitored the validation loss to prevent overfitting. We applied early stopping with a patience of 2 epochs to stop the training process if the validation loss did not improve. Throughout the training process, we collected the training and validation losses as well as the training and validation accuracies. These metrics provide insights into the model's performance and help in analyzing its learning behavior.

For The **Crop Recommendation and Support system “IoT-SACRSS”**, we are proposing a support system to recommend the most suitable crop to grow based on IoT sensors data obtained from the fields and to help the farmland owners to have precision agricultural insights. We have developed various machine learning models and selected the one with the highest accuracy. The system relies on a KNN machine learning model that predicts the most suitable crops to grow based on temperature, soil pH, NPK values, humidity, and rainfall rate and using fuzzy logic and knowledgebase data the system returns the top 3 crops that will give the maximum productivity. The support system provides data-driven recommendations for achieving optimal nutrient and environmental conditions to improve crop yield. It provides the farmer with soil health insights during the whole cultivation season and determines their land's nutrient needs based on the NPK values, the system recommends a customized mix of soil enhancers, such as biochar and compost.

We have used data augmentation techniques for machine learning models involving various approaches to enhance model performance. Firstly, we have used random sampling that involves duplicating rows or performing bootstrap sampling by randomly selecting rows with replacement to increase the dataset size. Secondly, Feature Engineering as Polynomial features and interaction features are created to capture non-linear relationships between variables. Binning discretizes continuous variables into distinct bins. Thirdly, noise injection gaussian (uniform noise) is added to feature values to introduce variability and improve model robustness.

After Preprocessing data, we tried a variety of machine learning classifiers on the dataset :

We started with a Decision Tree classifier that was trained and evaluated on the given dataset. The dataset was split into training (70%) and testing (30%) sets, and the classifier was trained on the training data using the "entropy" criterion. The accuracy of the classifier was measured using the testing data, and a classification report was generated to assess its performance in terms of precision, recall, F1-score, and support for each class.

Secondly, K Nearest Neighbors (KNN) classifier was employed and assessed on the dataset. The classifier was trained using the training data and evaluated on the testing data. The KNN classifier was configured with a value of 9 for the “n_neighbors” parameter, indicating that it considered the labels of the 9 nearest neighbors when making predictions.

And finally, the Random Forest classifier was utilized and evaluated on a given dataset. The classifier was trained using the training data and subsequently tested on the testing data. The Random Forest classifier was instantiated with 20 estimators and a random state of zero. After training the classifier, it was used to predict the target labels for the testing data. The accuracy of the classifier was calculated, and the obtained accuracy score was recorded.

The classifier recommends the most suitable crop to grow based on data obtained from the fields, but we seek to achieve more climate**-**positive recommendations. Using the approximate values of water usage, and carbon footprint data for each crop, the system provide the carbon footprint and water usage for the top **3** predicted crops for a particular scenario, this will help the farmers to take climate-positive farming decisions. The crop data, including the aforementioned values, has been collected from FAOSTAT. For example, the three main grain crops have carbon footprint per unit area (CFA) equal to (4871 ± 418 kg CO2-eq·ha−1) for rice, (2766 ± 552 kg CO2-eq·ha−1) for wheat, and finally the maize (2439 ± 530 kg CO2-eq·ha−1). The rice showed the highest carbon footprint and contribution to the total greenhouse gas (GHG) emissions, mainly due to their larger cultivated areas and higher fertilizer application rates.

The support system provides data-driven recommendations to get the optimal nutrients and environmental conditions to improve crop yield. It determines the land's nutrient needs based on the

NPK values, the system recommends a customized mix of soil enhancers, such as biochar and compost. Using the proposed algorithms, the system can recommend the needed nutrient amounts based on the number of acres & the NPK values. Entered readings are compared against the ideal benchmarks and margins of 10% are applied to assure an acceptable buffer allowance. Difference between the two would mean deficiency or extreme soil environment conditions and based on it, the algorithm would recommend the needed nutrient amounts, based on the number of acres (see **Algorithm** 1).

Algorithm 1 The Nitrogen Requirements

Read soil nitrogen readings (*Nitrogen Readings*).
Prompt the user to input the number of acres (AC).
Set the ideal nitrogen levels (I_N) to 50 ppm.
Set X as the input nitrogen value.
if X is within the range of $0.90 \times I\_N$ and I_N **then**
  Print "Your nitrogen levels are good, no need for additional nitrogen."
else
  Calculate the shortage (SH_N) as ($I\_N - X$).
  Calculate the shortage as a percentage of the ideal concentration of nitrogen ($Sh\_N\_Percent = (X/I\_N) \times 100$).
  Calculate the amount of N required (Req_N) as $(Sh\_N\_Percent/100) \times AC$.
  Prompt the user to select preferred nitrogen source (Urea or Compost).
  if Urea is selected **then**
    Calculate the final required N amount (Req_N_Final) as $Req\_N \times 2$.
    Print "Your land requires the addition of Req_N_Final pounds of Urea."
  else
    Set Req_N_Final as Req_N.
    Print "Your land requires Req_N_Final pounds of Compost."
  end if
end if

Moving to the second part of the project, the awareness app, we are proposing the AI-powered Smart Planting Guide. We have worked on identifying the plants type based on flowers and leaves characteristics and features. For the leaf classification model, we have developed a Linear Discriminant Analysis model to identify different types of plants based on leave shape, texture, and margins.

The leave dataset was represented as binary black images against white backgrounds. Three sets of features are also provided per image: a shape contiguous descriptor, an interior texture histogram, and a fine-scale margin histogram. For each feature, a 64-attribute vector is given per sample (see **Fig**. 7).

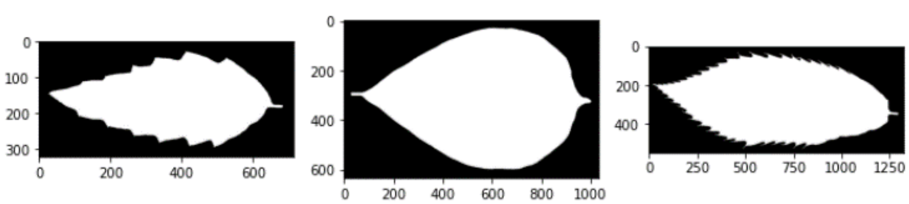


Fig 7. Sample images from the leave images dataset

Machine learning classifiers are algorithms used in supervised learning that can be applied to various tasks, including leaf classification. These classifiers aim to learn a mapping between input data and output labels, which can be binary or multi-class. Different classifiers use different techniques to separate the data into classes, such as decision trees, random forests, and Linear Discriminant Analysis.

In agriculture, machine learning classifiers can be used to classify leaves based on their features, such as shape, texture, color, and size. And in our case, which is classifying different types of plants using leaves, we have developed a Linear Discriminant Analysis (LDA) classification algorithm that finds a linear combination of features to separate data into classes. The steps involved are:

- Compute the mean value of each class.
- Compute within-class (S_w) and between-class (S_b) scatter matrices.
- Compute eigenvalues and eigenvectors of Sw^{-1} and Sb to find the directions of projection.
- Project the data onto the new subspace defined by the eigenvectors.

There are two types of scatter matrices that are computed in LDA. The within-class scatter matrix (S_w) measures the variability of the samples within each class, while the between-class scatter matrix (S_b) measures the difference between class means. These matrices are computed as in Eq.(1) & Eq. (2):

$$S_w = \sum_{i=1}^{k} \sum_{x \in C_i} (x - m_i)(x - m_i)^T \tag{1}$$

$$S_b = \sum_{i=1}^{k} n_i (m_i - m)(m_i - m)^T \tag{2}$$

For the flower classification, we have developed a fine-tuned (ResNet50) model and trained it on the flower's dataset . As the dataset was not large enough to train our model, we applied some data augmentation techniques. These techniques include random rotation, horizontal and vertical flipping, affine transformation, color jittering, random resized crop, random crop with padding, Gaussian blur, random perspective transformation, conversion to tensors, and normalization (see **Fig**. 8). These augmentations introduce variations to the images, enhancing the model's ability to generalize and handle diverse input data. By applying these transformations, the robustness and performance of the model trained on the flower dataset has improved.

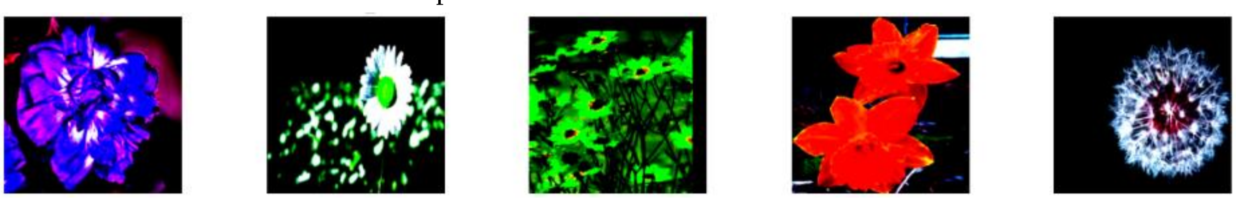


Fig 8. Sample of the augmented flowers images

The flower classification model takes advantage of the pre-trained ResNet50 model and adds a custom fully connected layer to perform classification. The last layer of the model is replaced with a fully connected layer consisting of two linear layers and a dropout layer with a probability of 0.3 to prevent overfitting. The first linear layer takes the output of the model and passes it through 128 nodes. The second linear layer takes the output of the first linear layer and passes it through the number of classes in the dataset. The model uses the Cross-Entropy loss function and the Adam optimizer. A step scheduler is used for the optimizer.

Phase III : Developing Together App & The Smart Farming Web Dashboard

To utilize these AI models and IoT-SACRSS system, we focused on developing two end-user products, Together, a mobile application to raise awareness among communities about climate change and provide a tool to make planting easier and a web dashboard to provide farms and agricultural domain with comprehensive tools that will enable them to reduce the impact of climate change on crop yields and increase productivity.

We have implemented all deep learning models in Python 3.9 programming language using TensorFlow and PyTorch Libraries on the Kaggle platform using NVIDIA TESLA P100 GPUs. After training the models, we have saved their best weights and developed a lightweight RESTful API using Flask to use our models and make predictions. Implemented python 3.7 using the PyCharm IDE and we deployed the backend code using AWS cloud services (EC2) and linked to the application. Android Studio has been used to develop the app using Flutter framework and dart language. MongoDB database system has been used to build the plant's documents.

The mobile application offers several features to encourage people to act against climate change. We have developed the app using Flutter as a cross-platform framework, connected to a backend API to receive the images, process them, infer, and return predictions. The app consists of 4 main features which are the AI-powered planting guide that can identify plant species from leaves, and flowers. This will help users to learn more about their plants and make planting easier. We have built our plant information database using MongoDB to provide a step-by-step guide on when to water the plant and all its information about how to care for it . The user can take a picture of his/her plant and the at the cloud will predict the plant type and based on the type; the data will be retrieved from the database. Each user has his own garden where he can add or remove his favorite plants.

The app introduces a community platform where people can share stories, tips, and raise awareness through posts and discussions like a social network. Users can upload posts with or without pictures, share tips and facts and interact with each other with likes and comments. Firebase has been used to Authenticate users using google accounts along with Firestore & Fire storage services to handle the user's data and social media platform data. Another feature of the app is the pollution report that will allow users to report polluting activities they observe around them feature will enable people to report polluting actions they see daily around them, such as burning rice straws, by using the user location and phone camera, the user can take a picture of the polluting activity to inform specialized authorities about it. And for the smart farming website, we have implemented the front-end using React J and bootstrap framework. For the backend a Django web application has been developed to make use of the AI models. It consists of 3 pages, dashboard, weed detection and disease detection.

4.3 Result Analysis and Discussion

This section presents and discusses the results obtained by the proposed models in detail.

- **ResNet50 Model**

Overall, our ResNet50 model achieved the higher accuracy among all the models that we have tried for the weed classification, with an average accuracy of **over 93%** across the 4 folds (see **Table**. 2). Table 3 presents a comparison between the models used in the experiment in terms of accuracy and where the proposed model achieved the highest accuracy across all the models used in the experiment.

Table 3. Validation Accuracy achieved

Model	Valid. Acc. Score
VGG19	0.8467 %
ResNet50	0.9879 %
CNN	0.7946 %

Table 2. Acc. & Loss achieved across folds

Fold	Train Loss	Val Loss	Train Acc.	Val Acc.
1	0.209469	0.191695	0.941731	0.943445
2	0.210408	0.191862	0.936304	0.939160
3	0.216815	0.192072	0.935161	0.943445
4	0.226620	0.215179	0.938018	0.943445

- **EfficientNetB2 Model**

The model building process focused on implementing an efficient model to classify the weeds and crops seedlings with high accuracy. As it was a challenge to extract features from the small seedlings, several deep neural network models, including MobileNetV2, VGG16, and EfficientNetB2 are proposed for transfer learning to classify images into their true classes (see **Table**. 4). The EfficientNetB2 showed the highest accuracy during training and validation with 97 % (see **Fig**. 9). Evaluation has been performed using Confusion Matrix (see **Fig**. 10).

Table 4. Validation Accuracy scores achieved by each model

Model	Validation Accuracy Score
MobileNetV2	0.9539 %
EfficientNetB2	0.9799 %
VGG16	0.9223 %

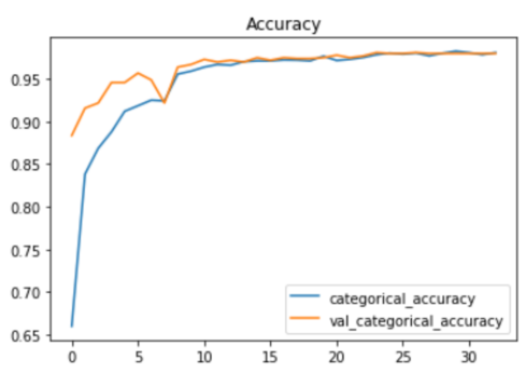


Fig. 9 Accuracy curve for train and validation.

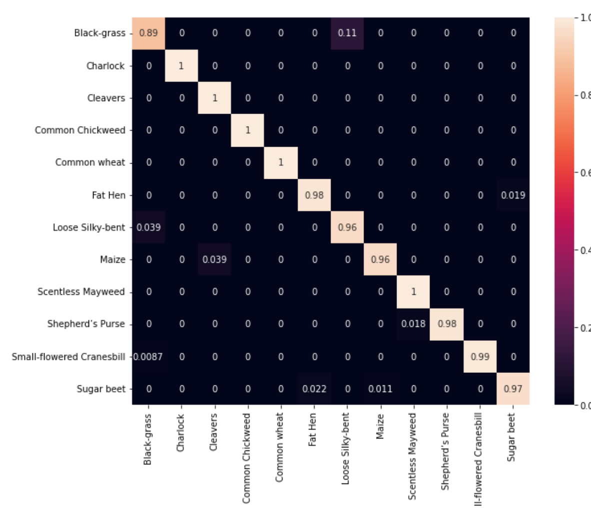
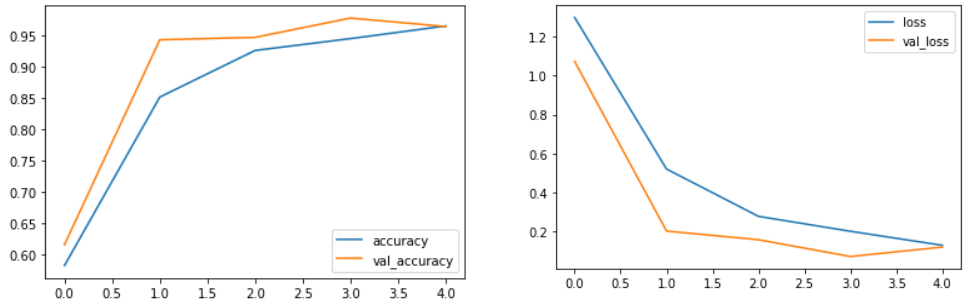


Fig. 10 Confusion matrix of the EfficientNetB2 model

2- Paddy diseases detection system (ResNet34)

The model exhibits remarkable capabilities in accurately classifying and identifying 12 distinct paddy leaf diseases. The model showed a high accuracy during training and validation (see **Fig**. 11).



(a) (b)

Fig. 11 Acc. & loss curves. (a) Acc. curve for train & valid. (b) Loss curve for train & validation.

3- Crop Recommendation (Random Forest**)**

The Random Forest Classifier showed the highest accuracy among the other classifiers (see **Fig**. 12).

For evaluation, we have used confusion matrix (see **Fig**. 13).

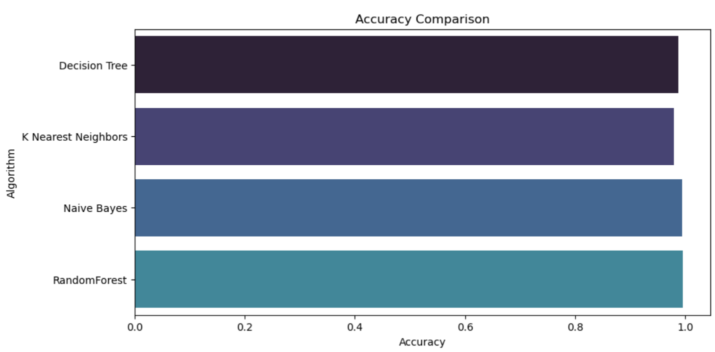


Fig. 12 Acc. comparison between classifiers

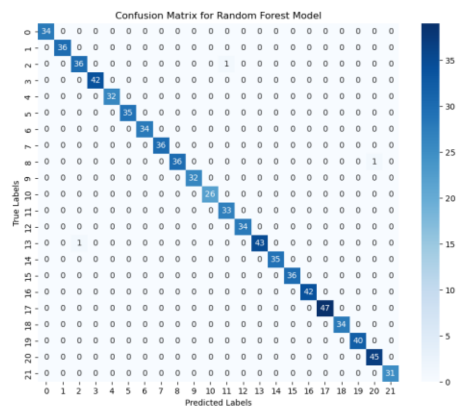


Fig. 13 Confusion matrix of the RF Classifier

4- Flower Classification (Resnet50**)**

Our fine-tuned ResNet50 model achieved the higher accuracy among all the models that we have tried for the weed classification, with an average accuracy of **over 93%** across 4 folds (see Fig. 14).

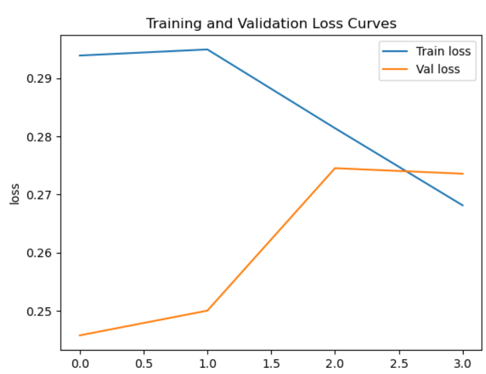


Fig. 14 Accuracy curve for train and validation for the last 3 epochs in the 4th fold

5- Leaves Classification (LDA)

The LDA classifier achieved ≅ 0.98 % for validation accuracy (see **Fig**. 15).

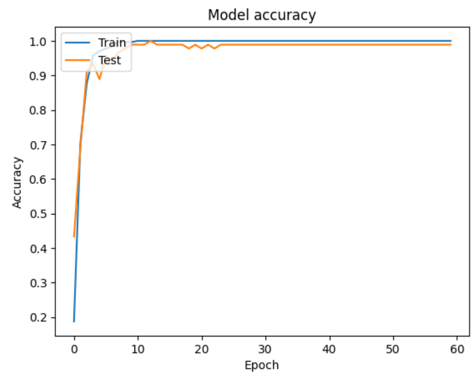


Fig. 15 Accuracy curve for train and validation

V. CONCLUSION AND FUTURE WORK

In conclusion, this project proposes an innovative solution to the challenges of climate change and agriculture through the development of the "Together" mobile application. The app aims to create awareness and motivate individuals to take small actions that contribute to reducing climate change. It provides various solutions and habits to monitor while motivating users to continue making positive changes and gaining more awareness through achievable methods and make planting easier.. The proposed smart farming system addresses the challenges of climate change by decreasing GHG emissions and increasing crop productivity through the expansion of woodland and soil and carbon farming. The app employs AI and IoT technologies to provide intelligent weed and disease detection systems and guide crop recommendations based on environmental conditions. The "Together" app offers a unique approach to build a community of people concerned with climate change by focusing on habit-building, empowering communities to increase resilience against climate change. In this way, the app offers a practical and accessible solution that can make a meaningful impact towards achieving sustainable agricultural practices and combating climate change.

5.1 Future Work

- Expanding the app's features and functionality: The app can be enhanced by adding new features such as an interactive map to showcase the global impact of climate change, personalized carbon footprint calculators, and gamification elements to the app to make it more engaging.
- Conducting further research and development: Further research can be conducted to improve the accuracy of the AI and IoT technologies used in the smart farming system. This could include developing more advanced sensors and algorithms to improve weed and disease detection and crop recommendations.
- Evaluating the app's impact: It would be valuable to conduct studies to evaluate the effectiveness of the "Together" app in promoting sustainable habits and contributing to climate change mitigation. User feedback can also be collected to improve the app's user experience and identify areas for further improvement.
- Scaling the app and farming system: The app and the smart farming system can be adapted and scaled to cover more plant types and crops.

- Integration of drones and IoT technology for precision farming: In addition to the current farming system features, integrating drone and IoT technology can help farmers to monitor crop health and identify issues such as nutrient deficiencies, pest infestations, and drought stress. The drone can be equipped with sensors and cameras that collect data on soil and crop health, which can then be analyzed using AI algorithms to provide farmers with actionable insights.

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VI. APPENDICES

Appendix A

The following images shows the empowering app features (**Fig**. 1, 2, 3, 4, 5, 6, 7, 8, 9)

Fig. 1 Create Post

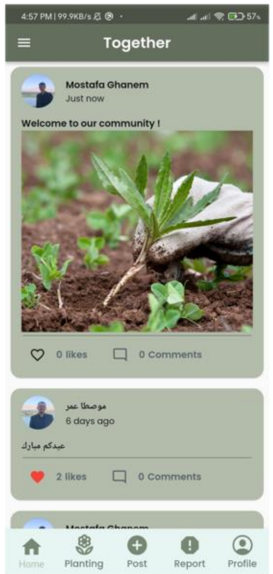

Fig. 2 Community

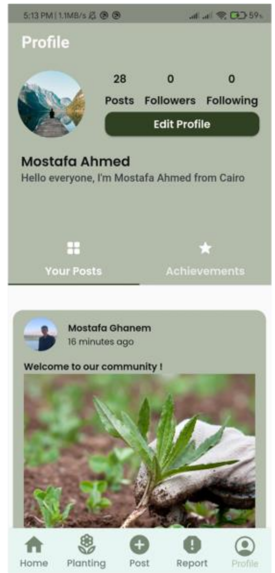

Fig. 3 User Profile

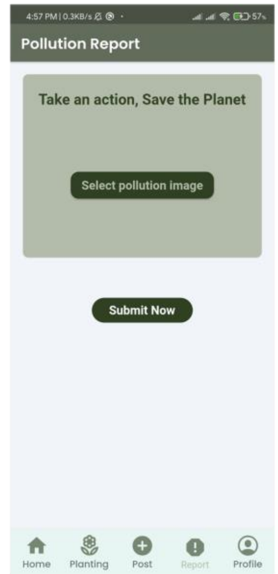

Fig. 4 Pollution Report

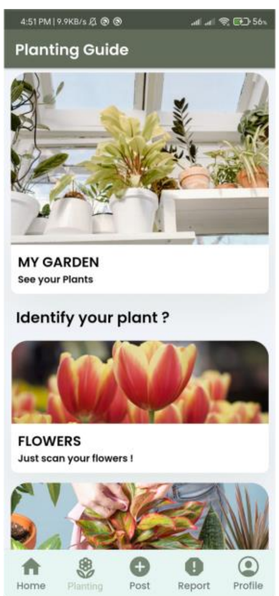

Fig. 5 Planting Guide

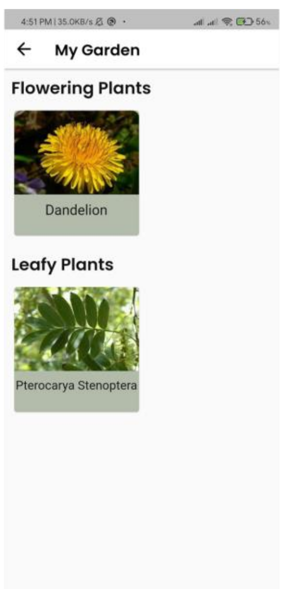

Fig. 6 Garden

Fig. 7 Plant details

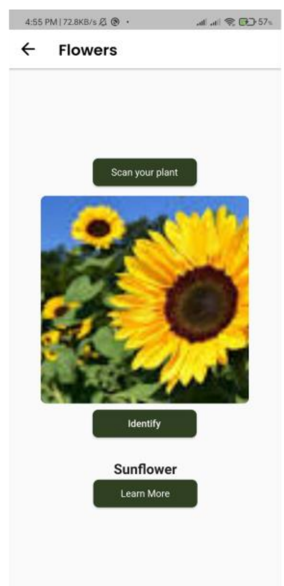

Fig. 8 Flower Identify

Fig. 9 Plant Info