Machine Learning-based Mobile Application for Weed Detection in Paddy Fields

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Abstract

In the context of Sri Lanka, where agriculture, particularly paddy cultivation, plays a crucial role, farmers face significant challenges due to weed infestation. Unlike some other countries that have embraced machine learning technologies to address these issues, Sri Lanka has yet to adopt such advanced solutions. To tackle the pervasive weed problem, a research initiative was undertaken to develop a mobile application capable of identifying weed types. The methodology involved utilizing Convolutional Neural Network (CNN) pre-trained models, namely ResNet-50, Inception-v3, and VGG16, along with the Google Colab platform for training the dataset. Among the three models, VGG16 demonstrated the highest accuracy, making it the chosen model to further the research. The primary goal was to achieve a superior level of accuracy in detecting weed species in rice fields. The research team focused on delivering a mobile application with a high level of accuracy to identify and classify weeds in paddy fields. The integration of advanced technologies, such as IoT and machine learning, aimed to provide Sri Lankan farmers with an efficient and effective tool to combat weed-related challenges in their agricultural practices.

Keywords: Weed detection, CNN, VGG16, ResNet-50, Inception-v3, Weed control methods

I. INTRODUCTION

Technology is being developed rapidly, constantly offering new solutions across various industries. Digital devices such as computers and smartphones have become essential tools in addressing everyday challenges. In the modern world, researchers and tech enthusiasts are continually creating systems and innovations by leveraging the latest technological advancements. As an agricultural country, in Sri Lanka, most of the farmers are struggling with the weed problem. The research is about the development of a machine learning based mobile application to identify the weed types in rice fields and provide weed controlling methods for the identified weed types. VGG16, InceptionV3, and ResNet 50 are the 03 Convolutional Neural Network (CNN) models that we used to train the image dataset. The mobile application was developed using the VGG16 model which gives the best accuracy in object detection. The research is based on the weed problem in Sri Lanka paddy cultivation and proposes a model with a higher level of accuracy for weed detection. In addition, it is planned to provide weed control methods for the identified weed species, and categorize weed control methods under organic (cultural, biological, physical, manual) and inorganic weed control methods with a short description of each weed species.

The target users are Sri Lankan farmers in both rural and urban areas, students, and the young generation interested in farming. In this research project, object detection accuracy is the key point and has the highest priority. Here, we used weed leaves in the image data set, and the accuracy level can be increased by using a large number of images.

In this work, the data set was collected by visiting the fields and capturing images of the found weed plants. The collected data set was trained on Transfer Learning technologies and three Convolutional Neural Network models (VGG16, Inception V3, ResNet 50) and found the best model as VGG16 according to the accuracy level and data loss.

Figure 01: Captured image data set

The technologies that were used for the project were Transfer Learning technologies, three

Convolutional Neural Network models (VGG16, Inception V3, ResNet 50), Keras, etc.

A. *Convolutional Neural Network (CNN)*

CNN is a part of the Artificial Neural Network (ANN) in deep learning. CNN can recognize the patterns of objects. CNN is designed explicitly for processing pixel data and has a large number of neurons that can self-optimize via learning. CNN consists of 5 layers.

B. *Transfer Learning*

Transfer learning is the use of a pre-trained model (a model that was trained previously on one problem) in some way on another second problem. In deep learning, transfer learning is a technique where one previously trained neural network model is used to solve another similar problem. Keras is a powerful open-source Python library for developing deep learning models that run on top of the machine learning platform TensorFlow. So, many pre-trained models are available here. VGG16, Inception v3, and ResNet 50 are selected from them.

II. RELATED WORK

Research article shows that weeds reduce the yield and quality of the farm harvest (Kamath, Balachandra and Prabhu, 2020). But in most cases, weed management is not followed. The research contains a technique that can be used for automatic weed detection and identification. Their proposed system was a computer vision-based automatic weed detection. In their application, weeds can be detected and identified and classified from digital images. According to their review, computer vision can be defined as a process of analyzing images and videos into meaningful interfaces. The proposed system can be used in the agriculture sector to identify plant classification and crop disease identification. According to the paper, India lost INR 1050 million because of the harvest losses. They created the dataset according to types of weeds. They collected the dataset using two digital cameras facing down towards the ground. Images were acquired from a Raspberry PI (RP OV56647) camera and stored in RGB color space in JPEG format. They used MATHLAB (R2018) to process images. In their research, they used a sample of 300 datasets, dividing them into training and test sets. They predicted outcomes on the test data and measured diversity using Yule's statistic. The study developed two MCSS models to classify paddy crops and weeds from digital images. Their proposed system can be applied to publicly available paddy crop data and aims to recommend appropriate herbicides for different weed types based on the classification results.

Bai et al. (2020) conducted their survey on object detection recognition and robot grasping based on machine learning. As this research is in the image processing field, machine learning plays a major role there. Convolutional Neural Networks realize the training of large scale image datasets. In this research, they applied machine learning, and machine vision to various image processing tasks, such as image detection, target detection, etc. The article contains information about how they use CNN to analyze and process. When compared with other image processing algorithms, CNN gives the advantage of having no processing requirements for detecting the target. Rechay et al. (2021) have focused on neural networks to detect disease in maize due to its economic significance. Weeds are a major problem in agriculture yield management. They proposed a smartphone application to identify maize crop disease in plants by using the dataset. As they mention, the detection accuracy is 83%. The work shows that they used the image Net dataset as a benchmark for computer vision. That dataset contains above 1000 items. Their defined model was developed using Python. The holdout methodology is used to evaluate results to separate the dataset to 80% training data and 20% for validating data. They did the testing part on a Ryzen 5 1500 6-core workstation. They develop the neural network model by developing two classes, healthy and diseased. They used the library TensorFlow Google developing model to design a deep learning model. The source library was written using Python. The backend was developed by using the TensorFlow backend. It is an open-source deep learning framework for developing mobile devices. The IDE that they used is Android Studio.

According to Roahn et al. (2011) in Sri Lanka, 50% of crop yields are reduced because of the weeds. Their research article shows how weeds affected paddy harvest and weed types. As they mentioned in the paper, there are 16 weed species.

According to Szegedy, Toshev and Erhan (2012) Image processing using Deep Learning Neural Networks is the most commonly used method in object detection. In the research article, the authors proposed a system to object detection in various classes using a formulation. Their proposed system is high-resolution object detection that can be used to detect images using DNN. The authors focused on DNN for object detection in a larger number of datasets and formulated a DNN based regression to get a binary mask as the result. They used DNN mask detection in a multiscale fashion to increase accuracy. CNN layers were used to detect images from the dataset. CNN regression layer was used to generate the binary mask. To get the most accurate output, the dataset images were divided into N number of pixels. The fixed size of the N is equal to d*d. According to the paper, the authors faced some challenges because of the image sizes and the limitation of the output cell size. If the image size with 400*400 and the d=24, the image can't be applied to the 16*16 cell. That problem was fixed using the multi-mask Robust localization. The proposed system was trained using 5 masks. The mask size is always larger than the image size. They used 1000 data sets for the model training, and the image set was divided into 60% negative and 40% positive datasets. The future work is to formulate the proposed system to use for a larger number of classes.

Sambolek and Ivasic-kos (2021) proposed system is a model that can be used in SAR operations to detect persons. Their research is based on an automatic person detection system using CNN and YOLO V4. According to the authors, the automatic object detection of images and person detection are commonly used. So the article is mainly focused on technologies such as R-CNN and YOLO V4. Related work shows that the YOLO V4 is the fastest and has high accuracy with small false detections. The researchers used CNN YOLOV4 to detect people, and as the dataset, they used the SARD data set. The paper describes that YOLO was selected as the tester because of its high accuracy. Also, the authors checked the transferring setting of YOLO V4 and used YOLO and Deep CNN to get the results. So the images in the dataset were divided into S*S frames and used the typical deep learning algorithms. The proposed system used a YOLO detector within a deep residual network with

53 layers. Also, the YOLO models were trained on the Google Colab service. In the experiment, they compared YOLOV4 with other testers, and the accuracy of the YOLO tester was 96%. Compared with the other testers, the best accuracy level is with the YOLO. So because of the accuracy level, they developed the system using the YOLO (SARD). The model was trained on 512*512 image resolution, but the 832*832 resolutions were used for the best results. For future work, they will develop a thermal camera to increase detection performance and recognize human activities.Zhang et al. (2021) proposed a system that can be used to GPR–B scanned images from rail infrastructure methods for object detection using faster RCNN, SSD, and YOLO V2. The system accuracy level is 97%. The authors have proposed a GAN-based deep learning framework to detect the hyperbolas automatically. The proposed framework has two parts: data generation and object detection based on deep learning. The main purpose of the system is to generate an image when the random noise is input. In the object detection part, the authors have proposed a one-stage detection model. The article shows that the CNN YOLO can be used as an object detection system to get more secure.Classification of a single pixel converts the problem of object detection into semantic segmentation (Lin et al., 2020). The authors mentioned that YOLO V3 has more accuracy than other test methods because it depends on multi-scale fusion. The proposed system is to remove anchors that detect objects based on two key points. One stage method is used because of the problem that occurs in the two stage object detection model. In this work, YOLO is used as the tester, and the image is divided into s*s cells. A cell center is called a grid cell. The grid cell was responsible for detecting the objects. Images were given with 511*511 size, and the output is 64*64 offsets. According to the authors CNN can be used to deep learning based well control object detection systems. The network framework that they used is like below.

From the research conducted by Kristo, Ivasic-Kos and Pobar (2020), they proposed a system of automatic person detection in thermal images. The used methodology to detect objects was CNN model training. According to this research, YOLO V3 was the fastest performance tester that can be used for object detection. To evaluate the best detection performance, they designed an original dataset and trained a deep learning model. The images were detected at the state of the art level. The proposed system was developed using an adaptive Boolean Based Saliency (ABMS) kernel with a YOLO detector. The data set was 4000 and the image size was 608*608 pixels. The system was trained without multi-scale training. The resulting output was a 90% person class with RGB images, and the model was trained on a 3000 training data image set. The performance of the model train was succeeded with the YOLO V3. And the trained dataset was COCORGB. In future studies, the authors will plan to develop an application to detect persons and non-human objects in different weather conditions.

Ratnasekera (2015) Reviewed how weedy rice is a threat to rice production, distribution, and strategies for weedy rice management. The research identifies weedy rice as one of the four most harmful weeds affecting rice fields globally. In the mid-1990s, it was first recognized as a problem in the Vavuniya, Ampara, and Batticaloa districts. This paper is valuable for our research as it discusses the unique traits of weedy rice. It highlights that weedy rice is difficult to distinguish from cultivated rice at the seedling stage due to their similar appearance. The limitation of this research paper is it does not talk about the weedy rice management practices. But it gives a clear idea about how weedy rice has spread throughout Sri Lanka paddy fields and its morphological and genetic diversity. This research paper is not directly related to our research topic, but it is helpful to study weedy rice.

Even though many individuals have been trying to provide a solution in recognizing weeds in the crop using various methods for several years, no system has made a business breakthrough yet. Considering this situation, Jaiganesh et al. (2020) proposed a model for plant identification by plant leaves using a deep learning technique - CNN classifier. They have used a dataset that is available on Kaggle. The dataset includes around 960 distinct plants from 12 different species, captured at various growth stages. The model achieved an accuracy of 82% on the training set, with a validation accuracy (for plant identification) of 86%.

One of the best CNN algorithms, YOLO, is good at solving object detection in the most simple and highly efficient way (Du, 2018). The paper describes the new directions of the YOLO, YOLO versions (V1, V2, etc.), CNN, the layers of CNN, CNN algorithms, and the limitations of CNN. Classification and localization and detection are the tasks of the image processing technology. In image processing model training, the most occurring problems are accuracy, speed and cost. Until 2012, CNN reduced the error rate from 26% to 15.3%. Then CNN developed in two directions called normalization and optimization. Further, the researchers have compared Faster R-CNN and YOLO V2. The performance of the detection systems has been compared with mAP (mean average precision) and FPS (frames per second). Compared with Faster R-CNN, YOLO has more advanced applications in practice. Fast YOLO is the fastest general-purpose object detector. YOLO's FPS 155 and its mAP can also reach up to 78.6, surpassing the performance of Faster R-CNN greatly. The comparisons confirm that the YOLO is a suitable algorithm for object detection research, and its performance, accuracy levels are higher than other detection systems. The limitation of YOLO is that YOLO struggles to generalize to objects in new or unusual aspects of ration or configuration. And there are shortages with its loss function errors. But YOLO can achieve high precision and keep real time for pictures with high resolution. YOLO is a unified object detection model. YOLO V2 provides state-of-the-art with the best tradeoff between the best accuracy and real time speed for object detection than other detection systems.

Overuse of herbicides in paddy fields leads to increased production costs and environmental pollution. To address this, it's essential to detect the location of rice seedlings and weeds for targeted weed management (Ma et al., 2019). The researchers propose a fast and robust image segmentation method for identifying rice seedlings and weeds at the seedling stage using SegNet, where these plants often overlap. The study focuses on two main objectives: introducing a semantic segmentation method based on encoder and decoder architecture, and comparing its performance with classical segmentation models, specifically FCN and U-Net. SegNet, a deep Convolutional Neural Network, is utilized for image segmentation, offering lower computational cost and higher precision compared to FCN. For the study, 28 RGB images were captured around 20 days after the rice seedlings emerged. The images, taken in paddy fields with weeds in early growth stages, were divided into smaller tiles, totaling 224 images. Of these, 80% were used for training and 20% for testing. The SegNet model was trained using transfer learning.

The results showed that SegNet achieved higher classification accuracy, with an average accuracy rate of 92.7%. In comparison, the FCN and U-Net models had average accuracies of 89.5% and 70.8%, respectively. In Sri Lanka, more than 142 weed species have been identified in rice fields. (Rao et al., 2017) The paper speaks about the methods (Manual, mechanical, tillage, mulching) of weed control used in South Asian countries. Manual weeding and submergence were the main weed control techniques used in Sri Lanka until the early 1960s. Then herbicides became more popular. As the single weed control approach is inefficient, Integrate Weed Management is needed to keep weeds below an economic threshold level.

The system proposed by Kulkarni and Angadi (2019) is about detecting weeds and crops using CNN and IoT. The proposed method is to train a large number of images of weeds and crops using

CNN. The trained CNN model is trained by getting images from the camera sent to the Raspberry pi. Raspberry performs image segmentation by dividing the image into small cells. Each CNN model classifies as weeds or crops. The system was trained using 250 image data sets. The accuracy rate is 85%, and the false ration is 7%. The proposed system consists of a Raspberry pi and a camera. The camera was used for image processing and segmentation. The results of the system are obtained with an average accuracy of 85%. So the proposed framework can be used by farmers to check whether the growth of weeds. The article shows that CNN can be combined and implemented in weed controlling to get excellent results. In the research of Liu et al. (2015) they used an algorithm consisting of two dimensional image information. The algorithm is focused on two main processes like convolution and sampling. The authors used the CNN subsampling method by sampling by time or space. The subsampling structure by time space was used to achieve some degree of scale and deformation displacement. The designed algorithm is based on gray image as input of 96*96 size, that turned in to 32*32 size of the images. The model was trained on the 7 convolutional layers and the results were more accurate.

The system proposed by Islam et al. (2021) is a machine learning algorithm to weed detection. The paper is organized with an overview of machine learning algorithms that can be used to weed detection in Australian Chili fields. The proposed system aims to detect weeds by using image processing and machine learning. The used data set was preprocessed using image processing, KNN based studies. Weed detection is the purpose of the proposed system. According to the paper, KNN offers a 63% percentage of RF 96%, and the SVM offers 94% accuracy in the weed detection proposed system. Their future work will be a deep learning algorithm to increase the accuracy of weed detection

III. EXPERIMENTAL WORKFLOW

In this section, the problem under investigation is explicated, providing context and emphasizing the study's significance. The existing knowledge gap is outlined, and the research objectives are articulated. By framing the problem, a foundation is laid for the subsequent sections, highlighting the relevance of the research.

A. Problem

In the present world, technology has involved every industry making their work more accessible and speedy. But when comparing to other industries, we noticed that no significant change can be seen in the farming industry. Especially in the Asia countries like Sri Lanka. Sri Lanka is considered as an agricultural country, and rice is the staple diet and the single most important crop in Sri Lanka (Senanayake and Premaratne, 2016). However, weeds in the rice fields are one of the major problems the Sri Lankan farmers face (Perera and Dahanayaka, 2015).

There are more than 120 weed species that can be identified that belong to 32 families (Gunasena, 1992). It is a challenging task to detect the weeds and select suitable weed control methods for each weed species. So, weeds have become a major problem to reduce the harvest of paddy cultivation. Further, the Sri Lankan younger generation is also interested in farming but they are not familiar with many weed species and the past weed controlling methods, and they have no knowledge or experience to continue their farming. So, we have identified that not having enough knowledge on weed detection and weed control methods is a reason behind this situation and the spread of weeds. Even though the Sri Lankan farmers are facing this problem from the earlier days, there is not enough support from modern technology to overcome this situation. So, it is clear that there should be more support from the technology to the Sri Lankan farmers and young generation, students, and researchers to identify the weed species in rice fields and suggest suitable weed controlling methods. The research is based on the above problems and proposes a model with a higher level of accuracy to weed detection. In addition, it is planned to provide weed control methods for the identified weed species.

B. Data Set Creation

The dataset was created using a Redmi Note8 48mp camera, Samsung S7 12mp camera, Samsung m12 48mp camera, and Nikon D750 camera. There were 3933 images belonging to 20 weed types. The data set was 3933 images belonging to 20 classes. In the dataset training process, the same data set was trained with the same parameters with all the 03 models. Google Colab idle environment was used as the idle environment to train the data set. The data set was created by cropping all images as squares and setting the pixel size to 224 x 224 for all and setting to auto-arrange white balance and high ISO normalisation. After that, the images were divided into 20 classes, and then those sets were divided into 2 groups as train and test datasets.

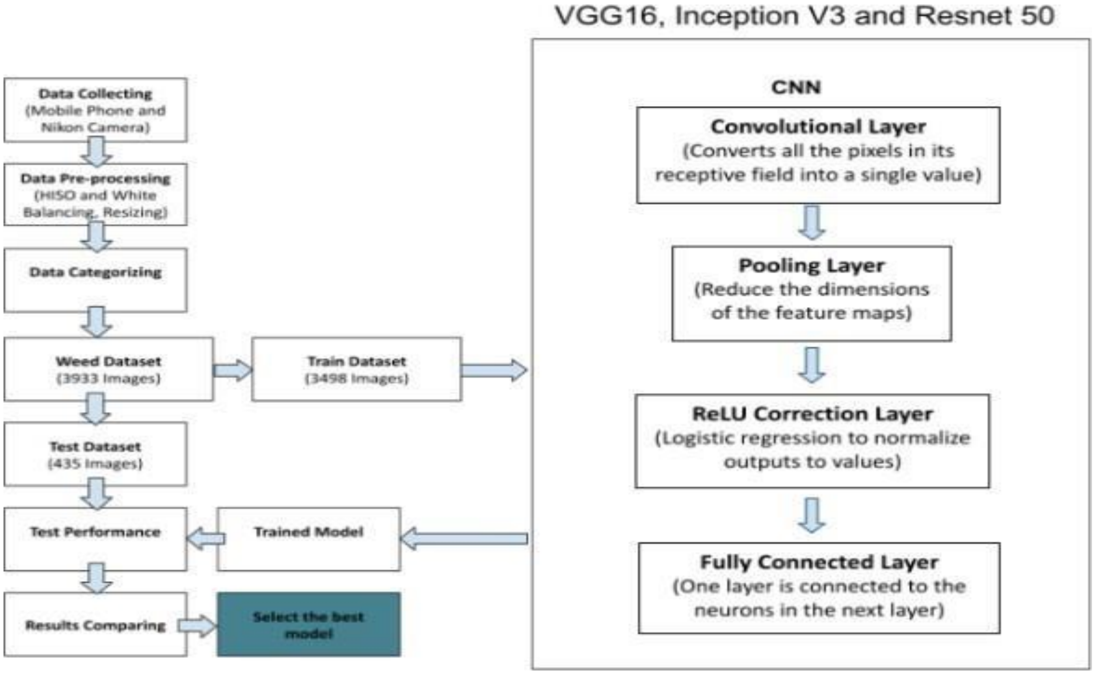

Figure 02: Model Training Flow Diagram

C. Data Set Training with Transfer Learning

VGG16

The selected data set was pre-processed before using this model as (224* 224 * 3). That model has 1,383 million trainable weights and 16 layers (convolution layers 3x3 filter, max pool layers 2x2 filter, 2 fully connected layers, and Softmax layer). The basic Architecture of a VGG16 is represented in Fig. 3.

Inception V3

Inception v3 is a pre-trained CNN model that Consists 48 layers deep{(Convolutional layers 4 [1*1], [3*3], [5*5]), MaxPooling layers[3*3], Fully connected layer 1} and 23,8 million trainable weights. It was trained on more than a million images in the ImageNet database. All images in the ImageNet database have a fixed size of 224*224 and have RGB channels (3) therefore we had to pre-process the images as we did in VGG16 (224 * 224).

ResNet 50

Microsoft introduced a deep residual learning framework (Resnet 50) to overcome the problem that occurs when adding more layers to a deep network may cause a higher training error rate. The [F(x)+x] formula makes shortcut connections to skip one or more layers. Then ResNets can get high accuracy when increased depth without training error.

IV. RESULTS

The image dataset was trained using the three models (VGG16, Inception v3, and ResNet50) two times. On the first try, only the VGG16 performed well and the other two models did not perform as expected. On the second try, both VGG16 and inception V3 performed well (accuracy of 98% and 99%), but the accuracy of ResNet 50 was not enough (75%). VGG16 was selected as the best model from VGG16 and Inception v3 by considering the accuracy and loss. Both models gave the best results but the validation loss of Inception V3 is higher than VGG16. And also the accuracy of the VGG 16

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model was 100%. So VGG16 was selected as the best model for the weed detection system.

Data Training Results

Data training Results with VGG16

- Validation accuracy - 75%
- Validation loss - 0.69
- Model loss - 0.63
- Model accuracy - 77%

Data training Results with Resnet50

- Validation accuracy - 98%
- Validation loss - 0.0464
- Model accuracy - 100%
- Model loss - 0.0025
- Epoch - 15

Data training Results with Inception V3

- Validation accuracy - 99%
- Validation loss - 0.1076
- Model accuracy - 99%
- Model loss - 0.0053
- Epoch - 15

B. Primary Detection Results

After considering the data training results, VGG16 model was selected as the image dataset training model. Results are shown in the TABLE.I

Table 01: Data Training Results

Model Name	Model Accuracy	Model Loss	Validation Accuracy	Validation Loss
Resnet 50	77%	0.63	75%	0.69
VGG16	100%	0.0025	98%	0.0464
Inception V3	98%	0.0053	99%	0.1076

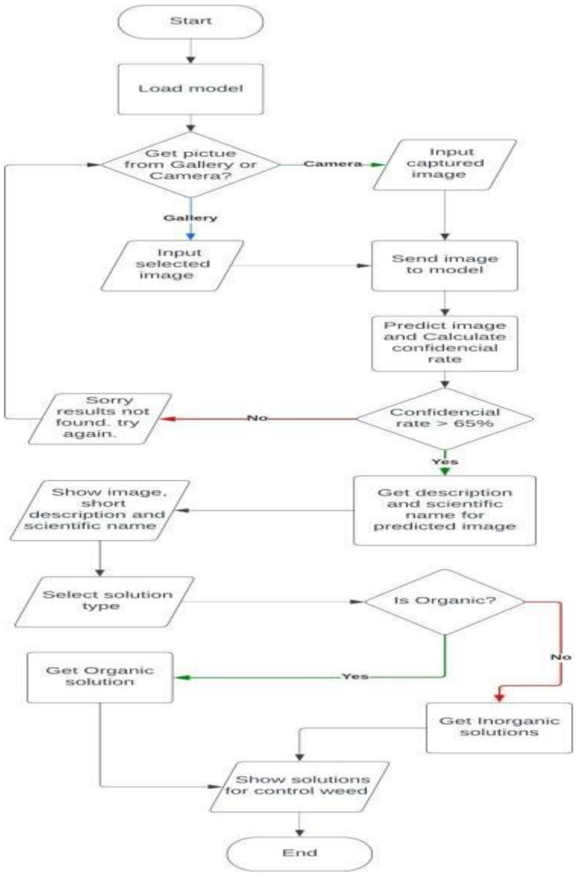

Figure 03: Mobile Application Data Flow Diagram

C. Mobile Application

In this research, we propose a mobile application designed to assist farmers in identifying weeds in agricultural fields. The app allows users to upload or capture images of weeds using their mobile devices. It employs image recognition technology to identify the weed type and provides detailed information on how it impacts the harvest, including potential yield loss. Furthermore, it offers step-by-step guidance on both chemical and organic methods to manage the weeds effectively. As paddy fields often lack internet connectivity, the dataset is stored locally within the application's database, ensuring farmers can access and use the app even in remote areas without a network connection. This solution aims to enhance farming efficiency by delivering real-time, actionable insights directly to farmers.

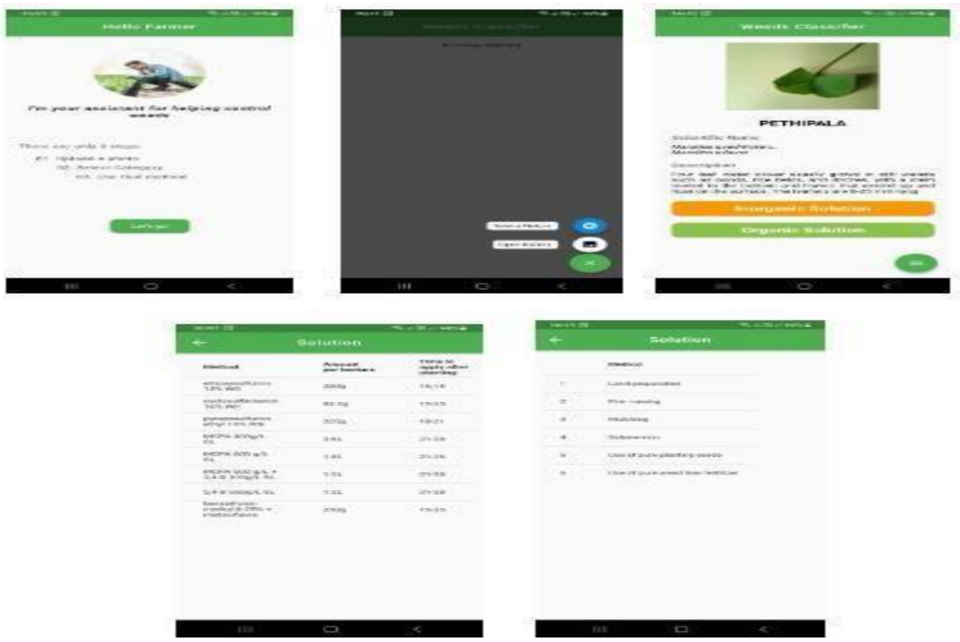

Figure 04: Mobile Application Interface

V. DISCUSSION

The primary objective of this project was to achieve accurate weed species detection in paddy fields. The developed mobile application, powered by the selected Convolutional Neural Network (CNN) model, successfully identifies six distinct weed types and offers tailored weed control methods for each. The literature review highlighted the longstanding challenges Sri Lankan farmers face in combatting weeds, with existing solutions relying heavily on traditional knowledge and experiences. The system created through this research serves as a significant support mechanism for farmers, the younger generation, students, and researchers engaged in weed detection and control methods. By leveraging advanced technology, the developed application not only addresses the immediate concerns of weed infestation in paddy fields but also contributes to the knowledge base within the agricultural community. This initiative represents a crucial step towards providing practical and efficient solutions to a persistent problem in Sri Lanka's agricultural landscape.

VI. CONCLUSION

In the course of this research, we proposed a machine learning-based system designed for the detection of various weed types in paddy fields, coupled with the provision of effective weed control methods. Drawing from pertinent literature, it became evident that Convolutional Neural Networks (CNNs) have proven success in object detection. In our study, the specifically employed VGG16 model demonstrated notable efficacy in identifying weeds in rice fields, achieving an impressive 97% validation accuracy, 0.0464 validation loss, 100% model accuracy, and a minimal 0.0025 model loss.

Through the developed application, we successfully implemented the VGG16 model to detect six selected weed types with high accuracy. Notably, the system can be further enhanced by expanding the range of detectable weed types. This involves refining the image dataset with higher-quality and more informative images. Subsequently, the dataset should undergo training with the VGG16 model, exploring optimal epoch sizes to maximize accuracy. This iterative process allows for the continuous improvement of the system's weed detection capabilities, making it adaptable to a broader spectrum of weed types in paddy fields.

VII. FUTURE WORKS

Here at this stage, the mobile application only shows 06 weed types from the selected weed types. The descriptions of those 06 weed types and the weed control solutions for them can be added within the same source code. For our future work, the application will be broadened by adding more weed types and we can create or link the application with external resources. But if the application was connected with such an external server, the ability to work offline would be lost. In this stage, the developed mobile application can provide offline services. Further, trying to enhance the user experience by making some changes to the designed user interfaces. For now, the application is only compatible with the English language, but it will be developed as compatible with the other languages.

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