Weed Detection Using Convolutional Neural Networks (CNNs)

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***Abstract*—In Agriculture, farmers plant different kinds of crops and grow them to sell or use, but apart from the intended crops there are also harmful weeds that grow naturally and compete with the crops for essential resources like nutrients, sunshine, water and space thus, resulting in poor quality and less yield of the crops. To Solve this recurring problem accurate and efficient weed detection is crucial as it helps in precision farming, however conventional detection and removal techniques are labour-intensive, time-consuming, and frequently ineffective. Following the recent advancements in deep learning and artificial intelligence many automated methods to tackle this problem have been developed. In this study, we propose a Convolutional Neural Network (CNNs) based deep learning model which uses TensorFlow framework and MobileNetV2 architecture to extract key features from captured plant images and automatically and accurately detecting and classifying the weeds and their species from the actual crop plants. The Deep Weeds dataset upon which the model is trained and evaluated, was acquired from GitHub. The Dataset is a multiclass weed species image dataset containing 17,509 labelled images across 9 distinct species. This study aims to advance intelligent and scalable automated precision agriculture techniques using a lightweight, efficient and easy to implement machine learning model that can be used by everyone in the agriculture industry.**

Keywords*—*Weed Detection, Convolutional Neural Networks, MobileNetV2, Deep Learning, Precision Agriculture, Image Classification, TensorFlow

I. *INTRODUCTION*

The recent development in deep learning and artificial intelligence technology has seen a quick rise in automated systems that can solve complicated real-world problems. Identifying and controlling weeds that have an impact on crop yield is one of the biggest problems faced by farmers in agriculture. Manually identifying weed is labour intensive, time consuming and prone to human mistake.

The proposed system that is Weed Detection Using Convolutional Neural Networks (CNNs) aims to develop an automated machine image-based weed detection and classification system using deep learning techniques. By analysing agricultural field images, the system identifies weed species and provides accurate predictions that can assist farmers and agricultural researchers in making effective crop management decisions.

Convolutional Neural Networks (CNNs) have emerged as one of the most popular architectures for image recognition and classification tasks due to their ability of automatically learning hierarchical features through convolution operations such as shape, edges, textures, objects and colour patterns directly from raw image data without the need for manual feature engineering. The systems effectiveness lies in its ability to automate the process of detection and classification of the weeds from the crops and the ability to combine the image acquisition, machine learning model and suggestion mechanisms into a single reliable, efficient and easy to use application , providing a solution to improve modern agricultural practices.

TensorFlow is an open-source framework that provides essential tools, community resources and libraries needed to easily and efficiently implement the Convolutional Neural Networks (CNNs) architecture that can run in any environment.

II. *LITERATURE REVIEW*

In the past few years, deep learning has been used a lot in plant and weed classification. Many researchers have worked in this area and tried different methods to improve accuracy.

Dyrmann et al. [5] utilised deep CNN models to categorise a plant species from field picture. They achieve a good level of accuracy. Furthermore, models eliminate need of manual feature design and simplifies the process, as CNN models automatically learn features from pictures. One issues in this field, requirement for a significant dataset. Gathering and taking the images of weed consume take quite a while. For this reason, Espejo Garcia et al. [6] adopted transfer learning. This approach reuses and train model again for classification once it has been trained on a large dataset. Method even helps when the available dataset is small.

Additionally, Chen et al. [7] used transfer learning to detect weed in cotton field. They also observed even when there are changes in lighting, background, or plant growth stages the model function effectively. This become crucial because farm photos are not always taken under

optimal condition.
In weed classification research, the deep weed dataset by Olsen et al. uses frequently. Images in this dataset has nine weed species obtain from Australian rangelands in actual outdoor conditions. For this project, we used this dataset because dataset is realistic and widely utilised by other scholars.
Base model used in our project is MobileNetV2 [3]. Which is lightweight CNN model, requires less memory and computation and provide accuracy. This model is better suited for mobile devices when we compare it to models like ResNet-50 and inceptionV3.

III. PROPOSED METHODOLOGY

Image collection, image processing using the MobileNetV2 CNN model and result display with simple recommendations are three primary components of the described system.

A. *Data Acquisition Layer*

The system in its initial stage collected images. Images can be taken in ways such as by drone, digital cameras, and smartphones. For training and testing purpose we used a publicly accessible labelled dataset, which can be found on various platform such as GitHub and Kaggle. Every image gets pre-processed, where it resizes, normalized pixel value and remove the basic noise. It is an essential phase since it ensures that every image is in consistent format, thereby helping in the model's proper training.

B. *AI and Image Processing Layer*

This is the main part of the system. A CNN model is trained on the labelled weed dataset. The CNN model itself learns simple features like edges, textures and colours and then combines all of them to recognize and learn more complex patterns such as leaf shape or plant structure. The main advantage is that the model learns all these features itself during training, so that no manual featuring is required.

C. *Detection and Decision Support Layer*

When the system finds a weed, it does not just tell you the name of the weed. The Detection and Decision Support Layer also tell you the confidence score for the weed image. This helps the user know how much the outcome can be trusted. The Detection and Decision Support Layer also suggest the user a few ways to deal with the weed. This makes the Detection and Decision Support Layer very helpful for farmers. Farmers need to be able to make decisions in the field, the Detection and Decision Support Layer give them the help they need.

D. *System Interfaces*

There are two ways in which the system can be use: by a website or a mobile application. On website you can upload pictures and look at the results and review history. Mobile application is more beneficial for farmers for the reason that they can take pictures and get the answer they need in real life. They use HTTPS to talk to the system, which make it safe for both website and mobile application. MYSQL or PostgreSQL like storage can be used for keeping all the past checks.

E. *Dataset*

Weeds dataset [2] was used to train and test our model. Dataset contains 17,509 labelled images of nine different weed species that was captured in outdoor condition in rangelands of Australia. Deep Weeds dataset [2] simulates real life field conditions because it includes variations in lighting, clutter backgrounds and different growth stages.

TABLE I: Deep Weeds Dataset Class Summary

ID	Weed Species	Images
1	Chinee Apple	1125
2	Lantana	1064
3	Parkinsonia	1031
4	Parthenium	1022
5	Prickly Acacia	1062
6	Rubber Vine	1009
7	Siam Weed	1074
8	Snake Weed	1016
9	Negative (nonweed)	9106
	Total	17,509

F. *Image Preprocessing*

We put images for some basic cleaning of the data before putting them into the ml model. Thus, we resized to 224x224 pixels that is the precise size which MoblieNetV2 operates with and compressed, the pixel value from typical [0, 255] range to [0, 1] simply by dividing by 255. This trick commonly used for helping the model learn a lot faster without getting “stuck”. We also perform some operations training data using data augmentation, such as horizontal flipping, zooming, and enhancing contrast, to make sure that AI could handle real-life like variation. As dataset is tiny this improves the model accuracy.

G. *Model Architecture: MobileNetV2 with Transfer Learning*

Using the MobileNetV2 model, TensorFlow framework and Keras for the image preprocessing we built our weed classification model. Since, MobileNetV2 is pre-train on the ImageNet, it has a wealth of general images feature that are excellent for starting.
A traditional two-step transfer learning approach is used for our nine-class weed identification task:
Step 1 - Training the classifier head alone: Froze (no weight changes there) the core MobileNetV2 layers and just trained the new classification head on top. This head consists of:

- Global average pooling to reduce those feature maps
- A dense layer with ReLU activation
- Dropout to fight overfitting
- A final SoftMax layer with 9 outputs (one per weed species)
- A batch normalization layer Step 2 - Fine-tuning the top layers:

After the head got trained, we unfroze few upper layers in the base model, added the class weights and retrained all with a significantly lower learning rate. Fine-tuning step enables the models tweak its greater-level feature, in order to identify our particular weeds better.

When adapting pre-trained models this two-phase methos is standard and works reliably across different datasets.

H. *Training Configuration*

We employ Adam optimizer for training. In Adam the learning rate gets modified automatically while training, making it simpler to use. Focal loss, commonly use loss function for multi-class classification problems. Further, we also utilise early stopping to stops the training if validation loss doesn’t improve till certain number of epochs, which help avoiding overfitting. Table II contain full list of training setting.

TABLE II: Training Hyperparameter Configuration

Hyperparameter	Value
Base Architecture	MobileNetV2 (ImageNet)
Input Image Size	224 × 224 × 3
Framework	TensorFlow 2.x / Keras
Optimiser	Adam
Loss Function	Focal loss
Output Activation	SoftMax (9 classes)
Regularisation	Dropout
Data Augmentation	Flip, Rotation, Zoom, Brightness, Shear
Dataset Split	70% / 15% / 15%

I. *Evaluation Metrics*

We used accuracy, precision, recall, and F1-score for measurement of performance of the model. Across each of nine classes, these were calculated and averaged. We likewise employed a confusion matrix to determine which weed species were confused with one another. Test set was kept apart from training and validation data, was used to calculate all results.

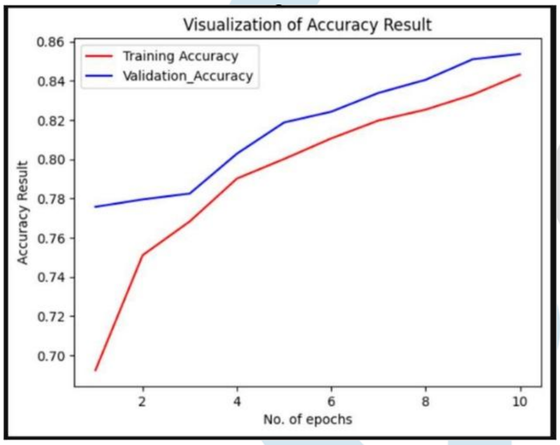
IV. RESULTS AND DISCUSSION

As previously explained, the MobileNetV2 model was trained and tested on the Deep Weeds dataset. To ensure that the results are fair and unaffected by the training data, another set of data was used for testing.
Model accuracy was good in the test set. In our case, we got better outcome by using transfer learning with ImageNet weights. Initially, only the additional layers were trained and later some of the base layers were also got fine-tuned. This step produces a significantly distinctive difference in performance.
While looking at precision and recall, both values are almost identical for majority of the weed classes. Therefore, the model is functioning quiet similarly for different categories. Dataset being almost balance can be one possible reason. Few errors were still there. From the confusion matrix, model sometime getting confused

between similar looking weeds, was observed. When lighting conditions were not proper or slightly different they model was getting confusion more.

Also, MobileNetV2 is much lighter as compared to models like ResNet-50 and InceptionV3. I noticed that it takes less time and computation but still gives almost similar accuracy. Because of this, it can be useful in real situation like farming where high-end systems are not always available. Overall, the results are quite decent. The CNN model with transfer learning works well for weed detection, although there is still some scope to improve in difficult cases. The accuracy of the model achieved can be seen in the figure 1.1

Fig.1.1



V. *CONCLUSION*

This paper presented a CNN based weed detection and classification system. It utilized MobileNetV2 and implemented in TensorFlow. The developed system was trained and validated using Deep Weeds dataset. Weed Identifying is a labour-intensive task, not suitable for large farms. Automating weed identification can save time, fasten farmers to take decisions and deal with the crop easily.

MobileNetV2 is a good balance between speed, size and accuracy. It is relatively small and fast. Additionally, using a lightweight network like MobileNetV2 allows the system to be deployed to a simple Raspberry Pi (which is quite useful in remote farming areas). Although the dataset is not large, the model was able to learn meaningful representations of the weeds using transfer learning. Training the network in two stages (first with the base model frozen and then with it unfrozen and trainable) turned out to be a good strategy.

The next step would be to implement the detection system on a mobile phone or edge device. This would reduce the dependency on being connected to the internet.

Overall, this paper makes a positive contribution to precision agriculture using artificial intelligence for weed detection and classification.

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