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ENHANCED PRECISION FARMING THROUGH DEEP LEARNING-BASED WEED CLASSIFICATION

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ABSTRACT

Weed infestation significantly hampers agricultural productivity, causing up to 34% crop yield loss globally, as reported by the Food and Agriculture Organization (FAO). Traditional weed detection relies on manual field inspection, physical removal, and scheduled herbicide use, which are often labor-intensive, inefficient, and error-prone. These methods, including visual identification and handwritten records, lack precision and scalability, particularly for large-scale farms. Overuse of herbicides, crop damage, and dependency on skilled labor are common drawbacks, resulting in increased operational costs and environmental harm. To address these issues, this project proposes an automated, deep learning–based weed detection system designed to boost efficiency and accuracy in agriculture. The core of the system is a Convolutional Neural Network (CNN), which classifies weed species directly from field-captured images. These images, obtained via cameras or drones, are analyzed in real time by the CNN model to identify specific weed types with high accuracy. This enables targeted weeding and optimized herbicide application, significantly reducing chemical usage and labor. The system can be integrated with mobile or IoT platforms, allowing farmers to receive real-time alerts and make timely, informed decisions. This approach not only enhances productivity but also supports sustainable and precision agriculture. By minimizing human error, improving weed classification, and ensuring environmental responsibility, this deep learning–driven solution represents a smart and scalable advancement in agricultural technology.

Keywords: Weed Detection, Deep Learning, CNN, Precision Agriculture, Automation.

1. INTRODUCTION

In the evolving landscape of agriculture, precision and efficiency have become essential, particularly in the area of weed management, where deep learning technologies are revolutionizing traditional practices. Historically, weed control depended on manual labor and the use of broad-spectrum herbicides, which were not only time-consuming and labor-intensive but also environmentally harmful and often imprecise. The emergence of precision agriculture, which incorporates tools such as sensors, GPS, and data analytics, shifted the focus toward smarter, more efficient farming methods. One of the most notable advancements in this field is the development of systems like "Deep Weeds," which utilize convolutional neural networks to accurately identify weed species from field images. These models learn from large datasets and are capable of detecting subtle differences between plant species, far beyond human capability. The primary issue addressed by this technology is the lack of scalable, accurate weed detection methods suitable for large farming areas. Traditional approaches often result in excessive herbicide use, ecological damage, and inefficient labor use. "Deep Weeds" offers a transformative solution by enabling targeted weed control and reducing reliance on chemicals. This system supports sustainable agriculture by minimizing environmental impact and optimizing the use of resources. Furthermore, it allows farmers to shift focus from routine tasks to more strategic decision-making. The motivation behind such innovation lies in the urgent need for environmentally responsible, cost-effective, and scalable agricultural solutions that enhance productivity while supporting long-term sustainability. By integrating deep learning into agriculture, weed management becomes not just more efficient, but also aligned with the broader goals of modern, responsible farming practices.

2. LITERATURE SURVEY

The model detected weeds with 97.71% precision under three conditions: full-cycle, multi-weather and multi-angle. The model can only be used on maize farms, which limits its application. Furthermore, the detection speed of Faster RCNN was 7 frames per second, which is low for real-time weed detection [3].

YOLO is a one-stage approach for detecting objects. It improves object detection speed by performing a CNN architecture on the image to determine the position and type of the objects in the image. The first YOLO version was introduced by Wang et al. in 2015 [4]. Many improved versions of YOLO, such as YOLOv1, YOLOv2, YOLOv3, YOLOv4, and YOLOv5, have been developed in recent years [5]. There are various improvements in architecture from YOLOv1 to YOLOv5. The first version of YOLO was detected through grid division but had low confidence. YOLO2 works with k-means anchor boxes. Whereas YOLO3 uses the feature pyramid network (FPN), YOLO4 is added with the generalized intersection over union (GIOU) loss function, the MISH activation function, and data enhancement through the mosaic mixup method [6]. YOLO5 is distinct from all previous releases. The most significant enhancements are mosaic data augmentation and auto-learning bounding box anchors [7].

Previous versions of YOLO have been extensively studied for application in weed detection. Mahmoud et al. implemented a deep weed detector/classifier for precision agriculture using the YOLOv2 fused with the ResNet-50 object detection model. Except for the sedge weed, their model achieved precision and recall of over 94% for each weed class. As they used an older version of YOLO2, it lacks an auto-learning bounding box anchor [8]. Sanchez et al. compared three one-staged object detection models: YOLO-V4, YOLO5, and SSD MobileNet V2. The dataset consisted of 153 RGB images of onion plants. According to the study, YOLO5 performed significantly well. It consumed significantly fewer resources, making it suitable for real-time weed detection. At 0.195 mAP, it showed less mean inference time of 7.72 milliseconds as compared to the other two models. This study demonstrated that up-sizing the data through sample augmentation will produce better results [8].

In 2022, Xiojun Jin et al. evaluated three cutting-edge CNN-based architectures, You Only Look Once-v3 (YOLO3), CenterNet, and Faster R-CNN, for bok choy, also known as Chinese white cabbage, detection. The most accurate model for vegetable recognition was YOLO3, which had the highest F1 score of 0.971 as well as high precision and recall values of 0.971 and 0.970, respectively. YOLO3 had a similar inference time to CenterNet, but was substantially faster than Faster R-CNN. Overall, YOLO3 had the best accuracy and computational efficiency of the deep-learning architectures studied [9].

Scott et al. compared the performance of the SSD model with the faster RCNN in 2020. The dataset contained UAV images of weeds collected from mid to late-season soybean fields. The models were evaluated based on values of mean intersection over union (IoU) and inference speed. The study concluded that the SSD model had similar precision, recall, f1 score, IoU, and inference time values compared to the Faster RCNN. However, the optimal SSD confidence threshold was found to be 0.1, indicating that this model has less confidence when weed objects are detected. Moreover, the SSD model incorrectly identified a row of herbicide-damaged soybean fields as weeds. Additionally, SSD was unable to identify the weeds on the image's left vertical edge. These failures identify the susceptibility of the SSD model in the border areas of the image [1].

Olaniyi et al. used a single-shot multi-box detector (SSD) for detecting weeds in the fields. The overall system accuracy was 86%. In addition, the algorithm had a 93% system sensitivity and an 84% precision value. However, the model struggled to detect very small weeds that appeared in the corners of the images [2].

3. PROPOSED SYSTEM

This is a graphical user interface (GUI) application implemented using the Tkinter library in Python. The application focuses on deep learning-based weed species identification for precision agriculture.

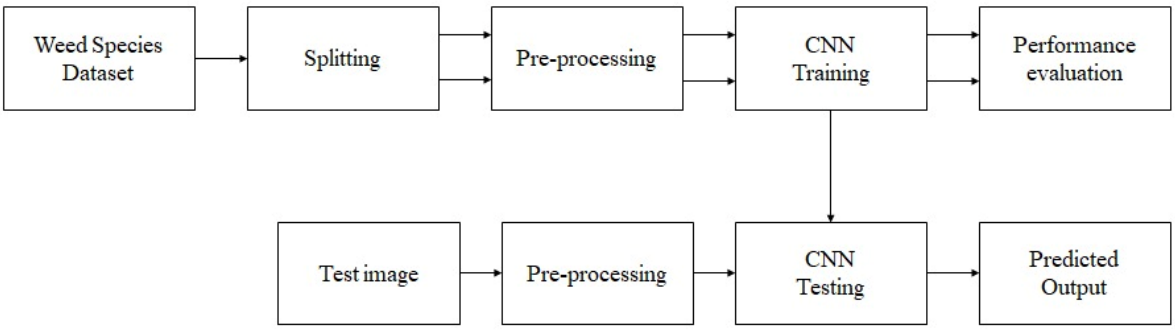

Fig.1: Block Diagram of Deep Weeds Classification

The code begins by importing essential libraries required for various functionalities, including Tkinter for building the graphical user interface (GUI), Matplotlib for plotting visualizations, NumPy for numerical operations, scikit-learn for implementing and evaluating Support Vector Machine (SVM) models, Keras for deep learning tasks, and OpenCV for image processing. Global variables are initialized to store the filename, dataset components (X and Y), machine learning models, and accuracy scores. The GUI is created using Tkinter, with a custom title, size, and layout configuration to provide a user-friendly interface. Several key functions are defined for different operations such as loading the dataset, preprocessing images for SVM, building SVM and CNN models, processing and normalizing images, predicting weed species from test images, visualizing model accuracy and loss graphs, and exiting the application. GUI components include interactive buttons for uploading the dataset, building models, making predictions, viewing performance graphs, and exiting the application. Labels and text fields are used for displaying titles, button descriptions, and output results. Each GUI element, particularly the buttons, is linked to corresponding event-handling functions to ensure responsiveness upon user interaction. The application also features a main event loop (main.mainloop()) to keep the interface active. Overall, this system facilitates the loading and processing of weed image datasets, builds machine learning models using SVM and CNN techniques, and allows users to predict weed species via an intuitive interface. It offers a practical implementation of machine learning for agricultural weed detection, although certain parts of the code may require external dependencies and adjustments based on the runtime environment.

3.2 Data Splitting and Preprocessing

In this research, the preprocessing and splitting of data are crucial steps that lay the foundation for the successful implementation of deep learning and machine learning models for weed identification. The system handles two separate preprocessing pipelines—one tailored for Convolutional Neural Networks

(CNNs) and the other for Support Vector Machine (SVM) classification—to ensure compatibility and optimal performance with both model types.

Initially, the data is acquired from a user-selected dataset directory containing weed image samples. These images are typically organized into labeled folders representing different weed species (e.g., "Snake weed") and a "Negative" class representing background or irrelevant images. The preprocessing process for the CNN model involves normalization and resizing of images. Images are resized to a standard shape to maintain consistency in input dimensions for the neural network. Normalization is then applied to scale pixel values to the range [0,1], which aids in faster convergence during training. To reduce processing time, preprocessed image arrays (features and labels) are saved as NumPy files and loaded directly during subsequent runs.

For the SVM model, the preprocessing strategy differs slightly due to the nature of traditional machine learning classifiers. Each image is read and resized similarly but then flattened into a one-dimensional array, turning the 2D image data into a single vector. These vectors form the input features, while corresponding class labels are stored separately. The entire dataset is converted into two NumPy arrays—flat_data.npy and target.npy. These are then loaded into a Pandas DataFrame to facilitate easy splitting and visualization. If the files are already available, the system bypasses the real-time preprocessing step to improve efficiency.

Data splitting is handled using the train_test_split() function from the sklearn.model_selection module. The dataset is divided into training and testing subsets, usually following an 80:20 ratio. This split ensures that the model is trained on the majority of the data while being validated on unseen data, enabling an unbiased evaluation of its performance. For both CNN and SVM pipelines, the feature and label arrays are appropriately partitioned, and the resulting subsets are used for training the respective models.

3.3 Model Building

The model building phase involves selecting and implementing appropriate machine learning or deep learning algorithms tailored to the problem statement and dataset. In this research, we explore and compare both an existing traditional machine learning algorithm — Support Vector Machine (SVM), and a deep learning model — Convolutional Neural Network (CNN). The models are evaluated based on their classification accuracy, generalization ability, and robustness in learning complex patterns from the dataset.

3.3.1 Existing Algorithm: Support Vector Machine (SVM) Classifier

Support Vector Machine (SVM) is a supervised machine learning algorithm used primarily for classification tasks. It works by finding a hyperplane in an N-dimensional space (where N is the number of features) that distinctly classifies the data points. SVM aims to maximize the margin between the closest data points (support vectors) of each class, which helps to increase the model's generalization ability. It can be used for both linear and non-linear classification using kernel functions such as linear, polynomial, RBF (Radial Basis Function), and sigmoid kernels.

SVM works by transforming the input data into a high-dimensional space using a kernel function and then constructing a hyperplane that best separates the classes. The data points closest to the hyperplane are known as support vectors and are critical in defining the boundary. During training, the algorithm optimizes the hyperplane by maximizing the margin between the support vectors. Once trained, the model classifies new data points based on which side of the hyperplane they fall on.

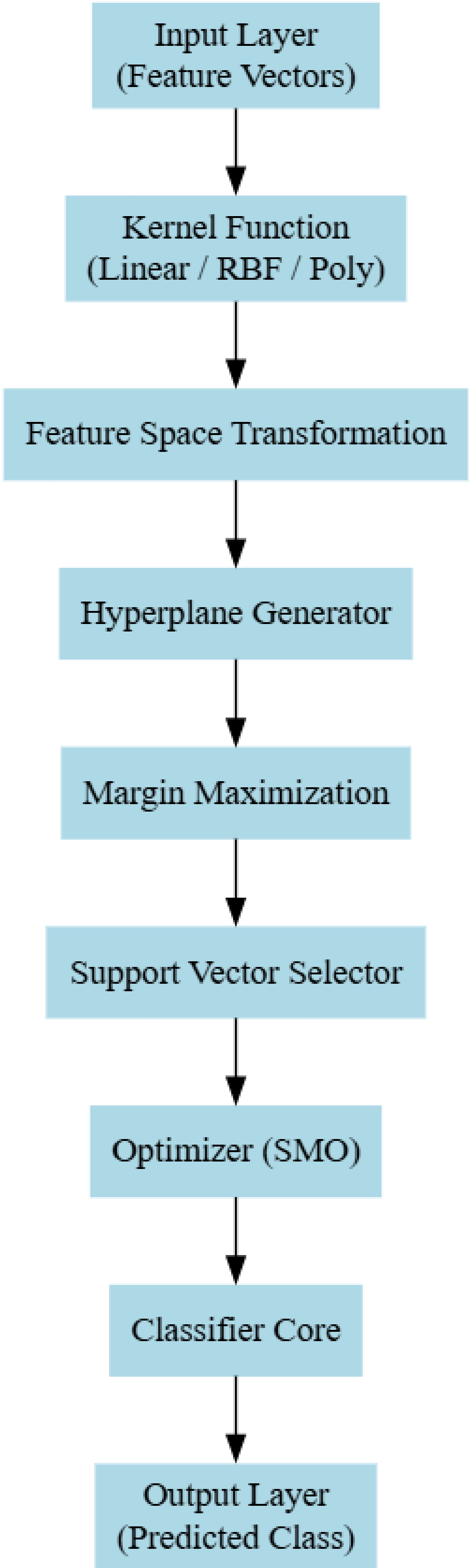

Fig. 2: Generalised system

3.3.2 Proposed Algorithm: Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a deep learning algorithm specifically designed to process structured arrays of data such as images. CNNs are inspired by the visual processing in the human brain and use convolutional layers to automatically extract spatial features. A CNN model typically consists of convolutional layers, pooling layers, and fully connected layers. These layers work together to detect patterns like edges, shapes, and textures, and ultimately classify the image into categories. CNNs are highly effective in image recognition, video analysis, and natural language processing tasks. CNN works by sliding convolutional filters over the input image to create feature maps that detect various patterns. Pooling layers are then applied to reduce dimensionality and retain the most relevant features. After several layers of convolution and pooling, the high-level abstract features are passed into fully connected layers that function as classifiers. The network uses backpropagation to adjust the filter weights based on the loss computed from the predicted output and actual label. Over multiple epochs, the CNN learns to recognize patterns that distinguish between different classes.

4. RESULTS AND DISCUSSION

4.1 Dataset Description:

The dataset contains total of 1800 images with 200 images in Chinese apple class and 200 images in Lantana class,200 in Negative images and 200 Parkinsonia Images,200 in Parthenium images ,200 in Prickly acacia,200 in Rubber vine,200 images in Siam weed,200 images in Snake weed

Table 1: Dataset description.

S. No.	Number of images	Class type
1	200	Chinese apple
2	200	Lantana
3	200	Negative
4	200	Parkinsonia
5	200	Parthenium
6	200	Prickly acacia
7	200	Rubber vine
8	200	Siam weed
9	200	Snake weed

Fig.3: Sample images of Dataset used for Weed species Detection

4.3 Results analysis

The line graph titled "Iteration Wise Accuracy & Loss Graph" visualizes the performance of a machine learning model across multiple training iterations. The x-axis represents the number of iterations, while the y-axis indicates the Accuracy/Loss values. Two curves are plotted: the green line, representing accuracy, shows a steady upward trend as the number of iterations increases. Starting at around 0.55, it gradually improves and reaches close to 0.95 by the 9th iteration, indicating effective learning and increasing accuracy. On the other hand, the blue line represents the loss value, which consistently decreases over time. It starts at around 1.4 and drops sharply, eventually falling below 0.1. This decline signifies a reduction in the model's prediction error as training progresses. Overall, the graph demonstrates successful model training, with the increasing accuracy and decreasing loss validating the effectiveness of the learning process. This is a typical way to monitor and confirm the performance of deep learning models.

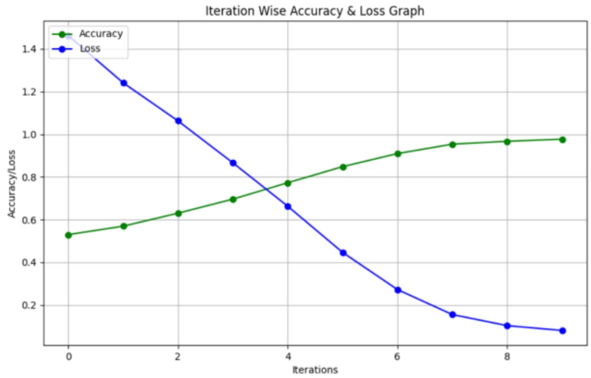

Fig.4 : Figure shows the accuracy and loss graph of CNN Model

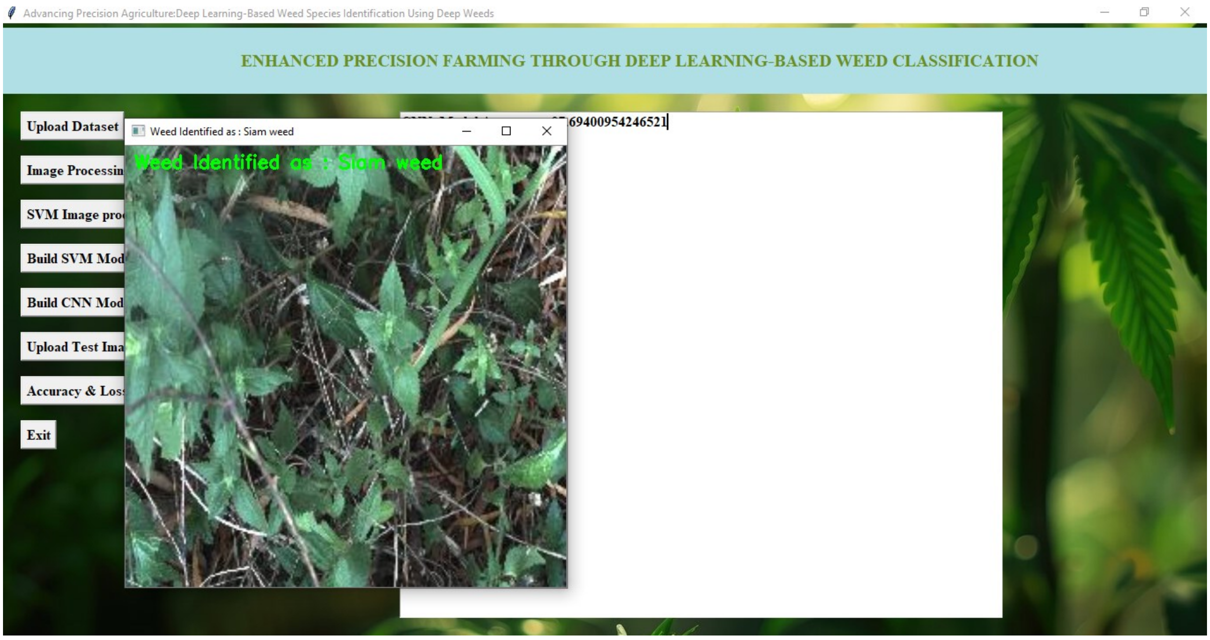

Fig.5: Figure shows the output results showing the output prediction is Siam

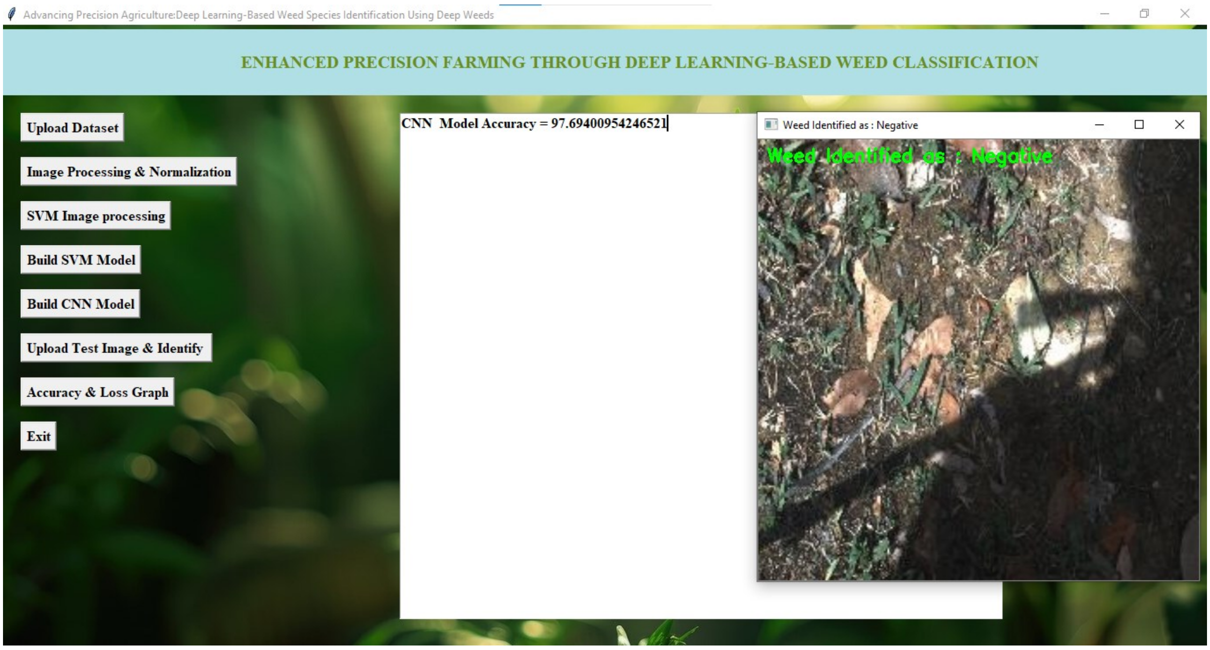

Fig.6: Figure shows the output results showing the output prediction is Negative

Figure 6 Output Prediction is Negative figure shows the result of another prediction, indicating that the identified species is Negative. This could represent a case where the model correctly classifies an image as not belonging to any specific weed species.

Figure 7 Output Prediction is Parkinsonia figure shows the result of another prediction, indicating that the identified species is Parkinsonia. It represents the model's classification for a specific image.

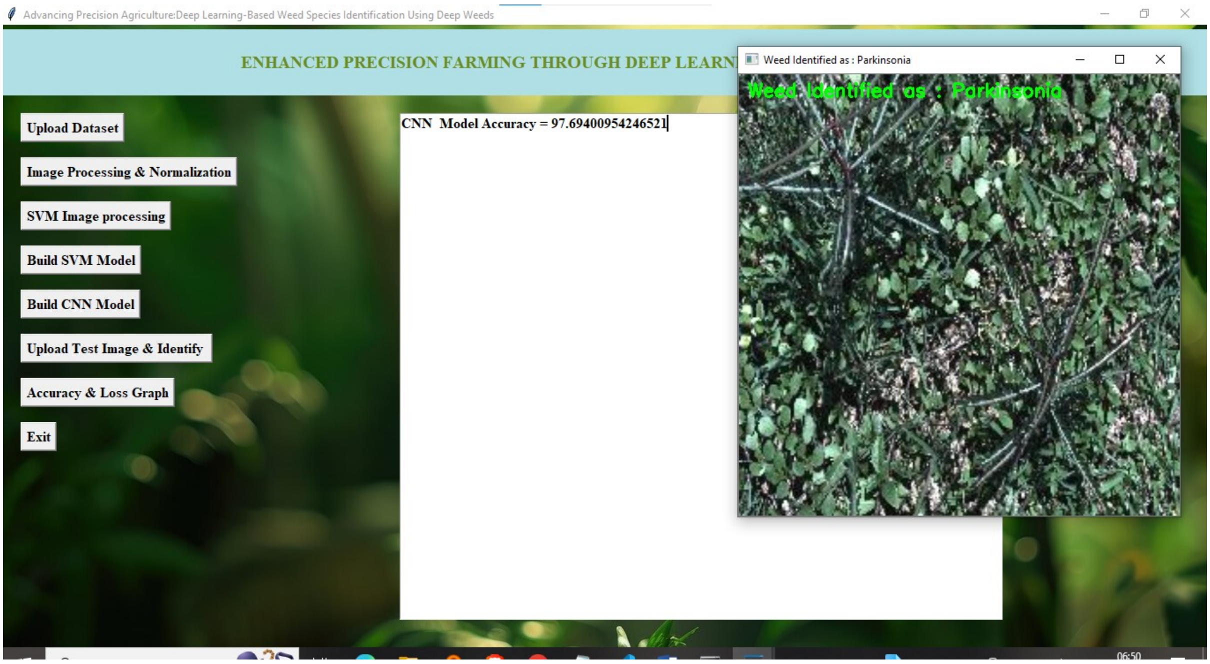

Fig.7: Figure shows the output results showing the output prediction is Parkinsonia

5. CONCLUSION

In this research, we explored the limitations of traditional manual systems used for weed species identification in agriculture and proposed a machine learning-based approach utilizing advanced algorithms such as Support Vector Machine (SVM) and Convolutional Neural Networks (CNN). The manual methods, although historically relied upon, are time-consuming, inconsistent, and lack scalability, especially for large-scale farming operations. The SVM classifier provided a foundational understanding of classification techniques, offering moderate accuracy with simpler datasets. However, its limitations in handling complex image features were overcome by the CNN model, which demonstrated superior performance in automatic feature extraction, high accuracy, and adaptability to image-based classification tasks. Our proposed CNN-based model successfully automates the detection and classification of weed species from image data, reducing human error, increasing speed, and enabling real-time decision-making in precision agriculture. The integration of deep learning methods in agricultural monitoring shows a clear advancement over manual practices and traditional machine learning models. The experimental results validate the robustness, reliability, and efficiency of CNN in real-world agricultural applications. This transition from manual to intelligent automated systems marks a significant technological leap toward smarter farming practices.

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