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Identification of Weeds in Wheat Crop Using Artificial Intelligence Techniques

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Wheat as an important cereal crop in India but presence of weeds results in significant damage in addition to insect pest and diseases. Weeds, which are unwanted plants that grow in agricultural crops, compete for essential elements like sunlight and water and are a major threat to food security. Conventional weed recognition approaches are very expensive, time consuming and require manual involvement by specialists. Researchers are actively investigating IT-based methods like computer vision and machine learning for weed identification. While models exist for identifying weeds in various crops, there is currently no specific model exists for weed identification in wheat crop. This paper proposed a mobile-based weed identification model using the ResNet50 deep learning architecture. The dataset used for training and testing the model consists of 1869 images of five prevalent weed species associated with wheat crop. After training, model demonstrated a notable accuracy of 93.25% on the validation dataset.

Keywords: Wheat; weed; CNN; Resnet50; mobile application.

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1. INTRODUCTION

Wheat is one of the most important cereal crops in India. Insects-pests and weeds cause significant damage to the crop that reduces the yield significantly. Weeds are undesirable plants that grow in agricultural crops competing for elements such as sunlight and water, causing significant damage to the crop and are major threat to food security however their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure.

A weed in a general sense, a plant is considered by the user of the term to be a nuisance, and normally grows as unwanted plants in human-made settings such as gardens, lawns or agricultural field, but also in parks, woods and other natural areas. Weeds become of economic significance in connection with farming, where they may damage crops when growing in fields and poison domesticated animals when growing on pasture land [1]. Weed infestation is one of the most important biotic factors limiting production and productivity of crops. Weed flora is not static and vary from field to field depending upon soil, environment and management factors.

Wheat crop is infested with a number of grass and broadleaf weeds. Depending on the weed flora, different management strategies, particular herbicide is applied. On the basis of cost of time effectiveness, the farmers prefer herbicides.

One of the main problems encountered in farming is the inability to recognize weeds among native species of plants. An accurate identification of weeds is of high importance which is however difficult. During the first six to eight weeks after seeding, weeds compete vigorously with the crop for nutrients and water. As result, annual yield losses arise in cultivated crops. The losses caused by weeds vary according to the type of weed, type of crop, and the environmental conditions involved. The proper identification of weeds is pre requisite for efficient weed management as herbicides which are selected based on the weed species infesting the field. The responses of herbicides also vary depending upon several factors such as time of application, method of application, etc. Effective weed management is important for a successful wheat production. Inadequate weed control can lead to significant yield loss and harvest problems.

The pre-prevailing weeds associated with wheat crop are *Chenopodium album* (Bathua), *Coronpus Didymus* (Pitpapara), *Convolvulus arvensis* (Hirankhuri), *Malva neglecta* (meadow weed or gogi sag), *Medicago polymorpha* (bur clover or burr medic), *Anagallis arvensis* (krishananeel), *Melilotus Alba* (Metha), *Poa annua* (Poa ghas), *Asphodelus tenuifolius* (Piazi), *Polypogan monspeliensis* (Lomar ghas) and *Argemone Mexicana* (Satyanashi).

The initiative is to start a mechanism of weed identification associated wheat crop keeping the principal issues in consideration that is encountered in farming is the ability to perceive weeds among native species of plants. An accurate identification of weeds is of high significance to reduce losses and with the outcome that increase the productivity. Weed plant's detection is important because these plants typically expend water and nutrients up to 70% which is provided to the crop.

In recent years, researchers have been exploring the use of IT-enabled techniques, such as computer vision and machine learning, for weed identification. Islam et al. [2] developed expert system for wheat crop management conveys information of 23 major weeds that affect wheat crop and its management information kept in its knowledge base. This system helps in identification of weeds of wheat through user's interaction. Ferreira et al. (2018) performed weed identification that related to soybean crop and differentiate these weeds between broadleaf and grass, for the purpose of applying particular herbicides for weed control. Jialin Yu et al. [3] developed CNN-model for identification of weeds related to Bermuda grass. Researcher also developed model for identification of disease as Mohanty et al. [4] developed deep CNN models for automatically identifying the disease from leaf images using an open-source dataset named PlantVillage37. Smith et al. [5] performed a study for weed classification in grassland using CNN and transfer learning techniques. Zhang et al. [6] concentrated on the broad leaf weed identification of wide leaf in pasture. Aitkenhead et al. [7] developed and compare two methods by which seedlings of specific crops and weeds can be distinguished from one another through digital imagery. Costello et al. [8] also detect Parthenium weed (*Parthenium hysterophorus L.*) and its growth stages using Artificial Intelligence. As of now different disease and weed classification model developed but no such model available to identification of weeds in wheat crop. In this context, I proposed the development of a mobile-based weed identification model using ResNet-50 architecture Koonce et al. [9] to accurately identify weeds in wheat crop. The mobile-based application is developed using the Android platform, and the user interface will be designed to capture images of weeds in wheat crop. The captured images are processed using the ResNet-50 model, and the results are displayed to the user in real-time.

2. MATRERIALS AND METHODS

In the process of weed Identification, wheat field of ICAR-Indian Agricultural Research Institute (ICAR-IARI) was chosen and images of weeds at different stages were collected (Table 1). The dataset presents five different types of weeds related to wheat crop. For training the machine we used a dataset containing 1869 weed images. All the images were converted into jpg format to accelerate the training process.

Table 1. Number of images per class weeds dataset

Weed Name	# images
Chenopodium album (Bathua)	339
Coronpus Didymus (Pitpapara)	287
Convolvulus arvensis (Hirankhuri)	343
Malva neglecta (Meadow weed or Gogi Sag)	469
Medicago polymorpha (Bur Clover or Burr Medic)	431
Total	1869

Before training the model, the images were preprocessed to enhance their quality and remove any noise. The preprocessing steps included resizing the images to a uniform size of 224x224 pixels, converting them to grayscale, and normalizing the pixel values. In the next step forward, preprocessed dataset divided in two parts for train and test dataset. Model is trained with Convolutional Neural network architecture with different parameter. With help of test dataset assessment of trained model has been performed in term of accuracy, precision recall. After that trained model deployed in smartphone application with test with ground truth data.

The proposed weed identification model was based on the ResNet-50 CNN, which was pre-trained on the ImageNet dataset. The last layer of the pre-trained ResNet-50 model was replaced with a new fully connected layer with five output neurons, corresponding to the five weed species. The new layer was initialized randomly, and the entire model was fine-tuned using the dataset of weed images. The model was trained using the Adam optimizer, with a learning rate of 0.0001 and a batch size of 32. The training was stopped after 100 epochs or when the validation accuracy stopped improving.

There are different approaches to check execution of our prepared CNN model. Accuracy is the most common metric used to assess the performance of a model (Fare et al. 2019). It relates to the total number of correct predictions among the total set of data. In a case of classification with different classes, need to recognize the average accuracy of overall accuracy.

A confusion matrix (Fig. 1) is a table that is often used to assessment the performance of a classification model. It presents a comprehensive view of the associations between the actual and

	Predicted Value		
Actual Value		**Positive**	**Negative**
	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Fig. 1. Confusion matrix

predicted classes in a given classification task. It comprises four key parameters: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Different performance metrices as accuracy, precision, recall and F1-score are calculated by confusion matrix parameters [10].

Main parameters of confusion matrix defined as:

True Positive (TP): The number of instances that were correctly predicted as positive.
True Negative (TN): The number of instances that were correctly predicted as negative.
False Positive (FP): The number of instances that were incorrectly predicted as positive.
False Negative (FN): The number of instances that were incorrectly predicted as negative.

With these four parameters, several performance metrics can be calculated:

2.1 Accuracy

It is a vital measure for checking how well a classification model predicts correct output. This metric calculates accuracy by dividing the number of correct predictions the model makes by the total number of predictions it attempts.

$$\text{Accuracy} = \frac{(\text{TP+TN})}{(\text{TP+TN+FP+FN})}$$

2.2 Precision

The proportion of true positive predictions among the instances predicted as positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$$

2.3 Recall

The proportion of true positive predictions among the actual positive instances.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$$

2.4 F1-score

When comparing two models with either low precision and high recall or vice versa, it becomes challenging to make a straightforward comparison. In such cases, the F-score proves to be useful. This score enables the simultaneous assessment of both recall and precision, providing a balanced evaluation of a model's performance.

$$\text{F1} - \text{Score} = \frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})}$$

Trained model is deployed in mobile application. Android studio development environment used to develop mobile application. This mobile application works on ground truth data and identifies related weed with highly precise result.

3. RESULTS AND DISCUSSION

In this research, we trained a weed identification model using the ResNet50 architecture to classify five different classes of weeds in wheat crops. The dataset used for training consisted of a diverse range of images depicting weed species commonly found in wheat fields. The trained model achieved an impressive accuracy of 93.25% on the validation dataset, indicating its effectiveness in distinguishing between the different weed classes. A mobile application has been developed that captures images of weeds and sends them to the deployed model for identification [11,12].

Confusion matrix (Fig. 2) can also be used as a visual representation of the performance of the weed identification model. It provides a detailed breakdown of the classification results of our weed identification model.

We also assessed the performance of weed identification model and computed the precision, recall, and F1 score to evaluate its effectiveness (Table 2). The findings revealed a precision of 92.79%, signifying that 92.79% of the predicted weed instances were accurately classified. Moreover, the recall, also known as sensitivity or true positive rate, was determined to be 93.10%. This implies that our model successfully detected 93.10% of the actual weed instances present in the dataset. Our model achieved an impressive F1 score of 92.90%, indicating a well-balanced performance in terms of precision and recall. The precision, recall, and F1 score collectively demonstrate the model's capability to accurately identify weeds in wheat crops. With a high precision, the model minimizes false positives by accurately distinguishing non-weed instances.

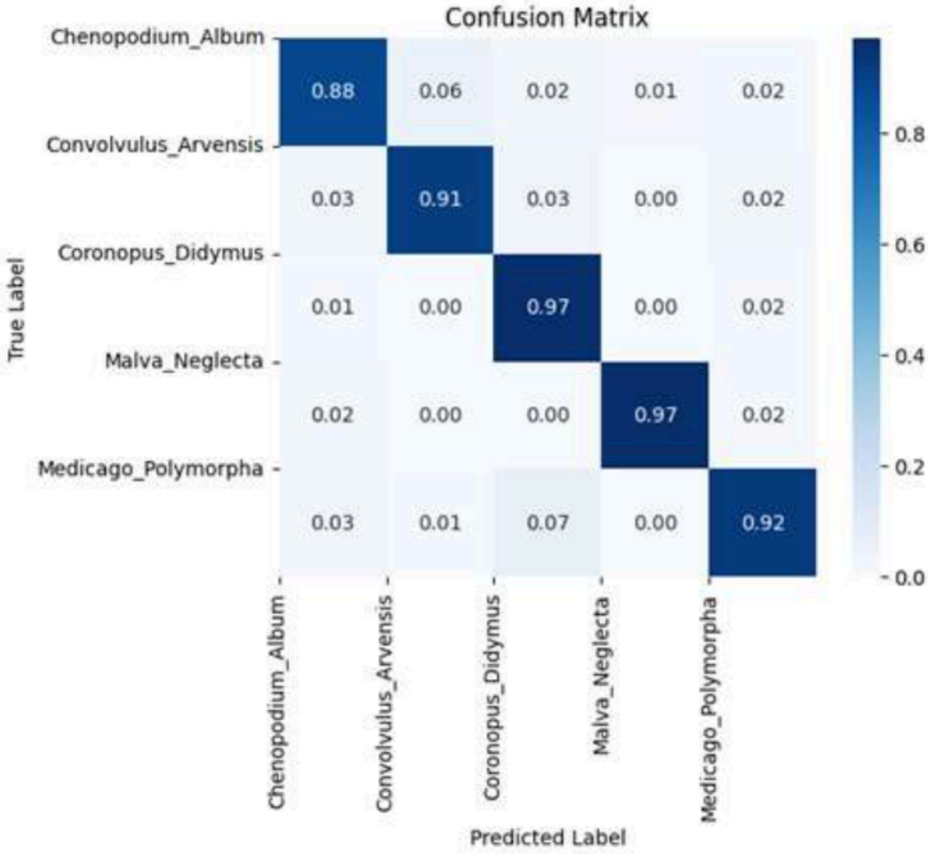

Fig. 2. Confusion matrix of weed identification model

Table 2. Performance measurement

Performance Measures	%Value
Accuracy	93.25%
Precision	92.79%
Recall	93.10%
F1-Score	92.90%

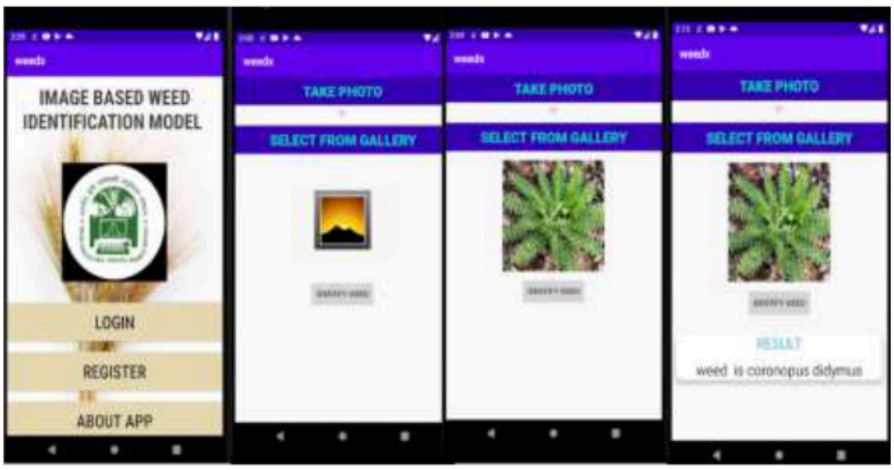

Fig. 3. Mobile Application weed identification model

A mobile app for weed identification typically includes several pages to provide users with a seamless and intuitive experience (Fig 3). The login page is the first page that users will see, where they can either log in to their existing accounts or sign up for a new account if they do not have one. The identification page is the main page of the app, where users can take a picture of a weed and submit it for identification. The results page is where users can view the results of the weed identification analysis. After users submit a picture of a weed, the app will analyze the image using AI models and return an accurate class of weed.

4. CONCLUSION

The successful development and deployment of weed identification model, along with the mobile application, opens up numerous opportunities for future research and application advancements. Our research demonstrated the successful training of a ResNet50-based weed identification model with high accuracy and performance metrics. The mobile application provides a practical and intuitive solution for farmers and agricultural professionals to identify and manage weeds in wheat crops effectively. There is potential for its application to be extended to include other types of weeds that are prevalent in wheat fields. By expanding the training dataset to incorporate additional weed species, the algorithm can be further refined to accurately identify and classify a broader range of weeds in other crops. By exploring these future directions, including expanding the weed species coverage, applying the algorithm to other crop types, and integrating it into IoT-based weed control systems, we can further enhance the effectiveness and applicability of the proposed method. This would ultimately contribute to sustainable weed management practices, improved crop yield, and reduced reliance on manual labor-intensive weed control methods.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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