Volume 01, Issue 02, December 2025 : 55-69 Received: Nopember 10, 2025. Revised: December 29, 2025.

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Android-Based Weed Identification and Herbicide Recommendation Using Convolutional Neural Networks

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Abstract: Weed infestation reduces crop yield and quality, while inappropriate herbicide selection often limits effective control. This paper presents the design and implementation of an Android-based decision-support application for weed identification and herbicide recommendation using a smartphone camera. Weed images are classified using a lightweight Convolutional Neural Network with a MobileNetV2 architecture optimized for mobile deployment. Herbicide recommendations are generated using the Cosine Similarity method to associate identified weed characteristics with suitable control agents. The system is modeled using the Unified Modeling Language (UML) to ensure modularity and scalability. Experimental results show that the proposed CNN model achieves a classification accuracy of 96%. The integrated on-device image acquisition and intelligent recommendation enable practical field deployment, providing an efficient tool to support weed management decisions.

Keywords: Android Application, Convolutional Neural Network, Herbicide Recommendation, MobileNetV2, Weed Identification

1. Introduction

In the era of rapid technological advancement, precision agriculture technologies—including Unmanned Aerial Vehicles (UAVs), remote sensing, artificial intelligence (AI), and advanced sensor systems—have become essential to enhancing productivity in the agricultural sector. These AI/UAV-based innovations enable site-specific crop management, improve decision-making, and provide practical, data-driven solutions to emerging challenges in crop production [1], [2], [3], [4]. One of the most persistent constraints in rice-based systems is weed infestation in paddy fields, which remains a major barrier to realizing the full yield potential of rice and other cereals. Weeds are recognized internationally as one of the leading biotic causes of yield loss, aggressively competing with crops for light, water, nutrients, and space, and in some systems contributing to average yield reductions on the order of 30–50% when not adequately controlled [5], [6], [7], [8]. In staple food crops such as rice and maize, unmanaged weed pressure can even lead to near-total crop failure under severe infestation, underscoring the critical need for integrating precision agriculture tools with intelligent weed detection and management strategies [2], [5], [9].

Weeds are unwanted plants that grow in agricultural areas and are widely recognized as the most serious biotic constraint to agricultural production worldwide, causing greater yield penalties than most insect pests and diseases [6], [10], [11]. They directly compete with food crops for water, sunlight, nutrients, and growing space, and often use these resources more efficiently, leading to strong suppression of crop growth and a marked reduction in yield potential and product quality [2], [6], [12]. At the global scale, weed infestation can reduce crop production by around 30–40% on average, and in many staple crops and low-input systems reported yield losses can reach 80–90% under severe or unmanaged weed pressure [10], [11], [13], [14]. Therefore, effective and timely weed control in food crops is essential to prevent these largely avoidable yield losses and to maintain food security [6], [10], [11].

Weed control can be carried out through several methods, including manual, mechanical, and chemical approaches. Among these, chemical control using herbicides is widely considered the main, most efficient, and fastest weed control tool, providing rapid and selective control over large areas at relatively low cost compared with other methods [15]. However, the sustainable use of herbicides critically depends on accurate weed identification and on choosing products and doses that match the specific weed flora and field conditions, since efficacy and resistance risks are strongly species- and dose-dependent [16]. Modern weed science therefore emphasizes the development of decision-support systems and precision technologies that integrate

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weed detection, species recognition, and dose–response information to optimize herbicide selection and application, reduce unnecessary chemical inputs, and limit environmental impacts [17]. Nevertheless, many farmers still lack sufficient knowledge to determine the appropriate type and rate of herbicide for the diverse weed species infesting food crops, and available information is often presented only in Latin nomenclature, which complicates practical identification and product choice. Therefore, a system that assists farmers in weed identification and herbicide selection within a decision-support framework is urgently needed to ensure both effective and sustainable weed control.

Previous studies on maize have mainly characterized weed communities through manual field surveys and phytosociological analyses, emphasizing species composition, abundance, and diversity rather than real-time digital support tools, and do not offer automated identification or integrated herbicide decision support for farmers [18]. More recent research shifts to computer-vision and deep learning, using UAV, UGV, or ground-based imagery and CNN models to automate weed detection, mapping, or susceptibility-based spraying decisions in various crops [19], [20], [21], [22], [23], [24], [25]. However, these systems usually operate at the level of weed presence, coverage, or herbicide-susceptibility groups (e.g., ACCase/ALS/synthetic auxin classes) and stop short of delivering species-specific, product-level herbicide recommendations to end users [21], [22], [24], [26].

In parallel, several AI-powered mobile applications have emerged in agriculture for disease, pest, or multi-threat identification in crops like wheat, maize, and tomato, demonstrating the practicality of deploying deep models on smartphones but generally focusing on diagnosis rather than explicit herbicide choice [27], [28], [29].

Addressing these limitations, this work proposes an Android-based CNN system that integrates automatic weed identification from smartphone images with tailored herbicide recommendations within a single mobile application. CNNs are leveraged for robust feature learning and species recognition in complex field conditions [18], [19], [20], [23], while the mobile platform provides an accessible, in-field interface comparable to other successful AI-agro apps [3], [9], [12], [14]. Herbicide options are then matched to identified species via a similarity-based recommendation engine, bridging the gap between image-based weed recognition and actionable chemical control guidance for farmers [27], [28], [29].

2. Related Works

Traditional weed management in maize has relied on broadcast herbicide application and manual scouting, which are labor-intensive, environmentally unsustainable, and poorly suited to site-specific control [30], [31], [32]. More recent work has increasingly leveraged computer vision and deep learning for automated weed detection, yet most systems still operate at the level of weed presence or cover and do not deliver species-specific herbicide recommendations to end users [30], [31] [33],

2.1 Weed Detection and Mapping Using Deep Learning

Deep learning–based weed detection has been widely explored in both ground and UAV imagery for site-specific weed management. Surveys and reviews show that CNN-based object detection and segmentation (e.g., YOLO, Faster R-CNN, U-Net variants) can accurately distinguish weeds from crops and support precision spraying or robotic weeding [30], [31], [32], [34], [35], [36], [37], [38]. Many studies demonstrate high mAP and real-time performance for detecting weeds in maize, wheat, and other crops, including early-stage maize weeds and intra-/inter-row detection [35], [39]. Recent work also targets multiple species and growth stages and proposes large benchmark datasets for weed–crop recognition [37], [38], [40], [41]. However, these systems typically output class labels or weed coverage maps to drive smart sprayers or robots and do not translate detections into explicit herbicide product and dosage recommendations [31], [33].

2.2 Precision Weed Control Technologies

Several works integrate deep learning with sprayers, robots, or laser systems to reduce herbicide usage via site-specific actuation [25], [33], [40], [42], , [43]. Smart sprayers use YOLO-type detectors or DCNNs to trigger selective spraying and may map weeds according to herbicide susceptibility categories rather than individual species [25], [33]. Review papers emphasize that current precision weed systems largely stop at detection and actuation, with intelligent decision-making (e.g., species-specific herbicide selection, dose adjustment, label and

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crop-safety constraints) still identified as a key future direction [30], [31], [32], [34], [40], [42], [43].

Across this literature, deep learning has markedly improved automatic weed detection in images and enabled site-specific spraying, but weed information is usually reported as presence, density, or generic species classes; and the output is rarely integrated into species-specific herbicide recommendation engines, particularly in forms accessible to farmers on mobile devices [32], [33], [40], [42], [43].

The proposed work addresses this gap by implementing an Android-based CNN system that not only identifies weed species from field images, but also couples these identifications with tailored herbicide recommendations within a single mobile application, thereby tightly linking image-based recognition to actionable chemical control decisions at farm level.

3. Research Method

The methodology of this study consists of several stages, including data collection, data preprocessing, model training, system design, and testing.

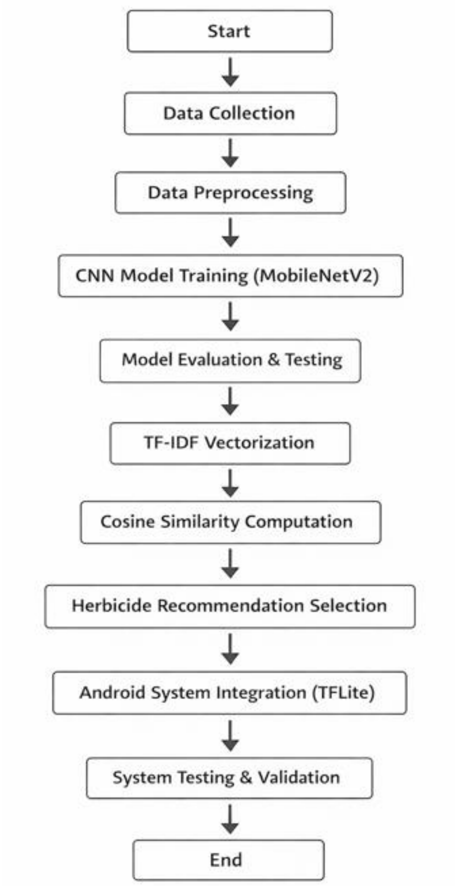

Figure 1. Research Method Diagram

The research process begins with weed image data collection, followed by data preprocessing and CNN model training using the MobileNetV2 architecture. After model evaluation, the identified weed species are transformed into TF–IDF vectors and processed using cosine similarity to generate herbicide recommendations. Finally, the trained model is converted to TensorFlow Lite format and integrated into the Android application for field deployment and system validation.

3.1 Data Collection

The first stage involves data collection. The dataset consists of weed images in JPG format. Image acquisition is performed by directly capturing photographs of each weed species using the primary camera of a POCO X3 NFC smartphone with a 64-megapixel resolution. This study considers ten weed species commonly found in agricultural fields, along with one “No Weed” class containing randomly selected images. The selection of weed species and corresponding herbicides is based on the Registered Agricultural and Forestry Pesticides handbook published by the Directorate of Fertilizers and Pesticides (2014). The dataset is divided into 70% for training and 30% for testing.

Table 1. Weed Image Dataset Distribution

Weed Class	Training Data	Testing Data
Alternanthera Philoxeroides	126	54
Ludwigia Octovalvis	126	54
Commelina Diffusa	70	30
Ipomoea Aquatica	91	39
Euphorbia	109	47
Pistia Stratiotes	154	66
Acalyphia Indica	81	35
Cleome Rutidosperma	79	34
Mimosa Pudica	81	35
Eleusine Indica	98	42
No Weed	123	53
Total	1138	489

3.2 Data Preprocessing

Data preprocessing is a crucial stage that prepares image data for effective use in convolutional neural networks (CNNs), ensuring consistent input size, format, and quality to improve training stability and performance [44], [45], [46], [47]. Typical steps include resizing images to a fixed resolution (e.g.,

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224 × 224 pixels), color-space conversion, and the application of data augmentation techniques [44], [45], [46], [48], [49].

Data augmentation increases the quantity and diversity of training data by generating modified versions of existing images, which is especially important when labeled data are limited [44], [45], [50]. By expanding and diversifying the dataset, augmentation helps CNNs mitigate overfitting, improve robustness, and achieve better generalization to unseen data [44], [47], [48], [50]. These augmented samples often incorporate variations in viewpoint, illumination, and orientation that may not be sufficiently represented in the original dataset, thereby better reflecting real-world deployment conditions [44], [50].

Commonly used augmentation operations include geometric transformations such as rotation, cropping, scaling, translation, and horizontal or vertical flipping, as well as photometric transformations such as brightness and color-intensity adjustment [44], [45], [47], [48], [50]. These techniques have been widely shown to improve performance in image classification, detection, and medical image analysis tasks by simulating realistic variations in object pose, scale, and lighting and thus enhancing model adaptability and generalization capability [44], [47], [51], [52].

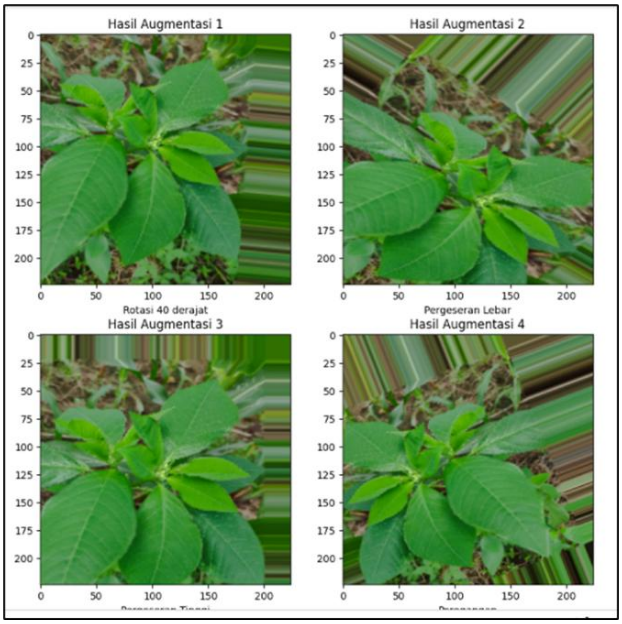

Figure 2. Data Augmentation Results

3.3 Training

After data preprocessing, the dataset is used for model training. In this study, the MobileNetV2 architecture is adopted as the CNN model, as it is specifically optimized for deployment on mobile devices such as Android smartphones. Model training refers to the process by which the CNN learns relevant patterns from the input image data. The training procedure is conducted for 20 epochs and employs the EarlyStopping callback from tensorflow.keras.callbacks. Early stopping is configured to monitor the validation accuracy (val_accuracy) and terminate training if no improvement is observed for five consecutive epochs, with the restore_best_weights parameter set to True. This ensures that the final model retains the best-performing weights achieved during training. After completion, the trained model is converted into TensorFlow Lite (TFLite) format for efficient integration into the Android application.

3.4 System Design

The system design in this study is developed using Unified Modeling Language (UML). UML is a standardized modeling language used to represent the structure, functionality, and interactions of a system to be built. The UML diagrams employed in this research include the Use Case Diagram and the Activity Diagram.

3.4.1 Use Case Diagram

The Use Case Diagram is used to describe the expected functionality of the software system from the user's perspective. It illustrates the interactions between the system under development and the actors or stakeholders involved in the system.

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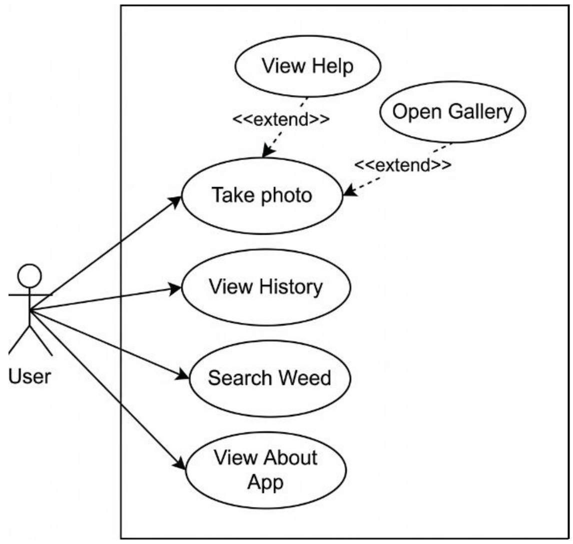

Figure 3. Use Case Diagram

In the Use Case Diagram shown above, the Capture Photo function allows users to access the camera and take images directly. Within this function, a Help option is provided to display guidance on how to properly capture weed images, along with a Gallery option that enables users to select images from the device gallery. In addition, the main menu includes features for viewing weed identification history, searching weed information, and accessing details about the application.

3.4.2 Activity Diagram

An Activity Diagram is a type of diagram used to represent workflows or activities within a process. It helps model the sequence of actions or activities that occur in a particular process or function, either in software-based or non-software-based systems.

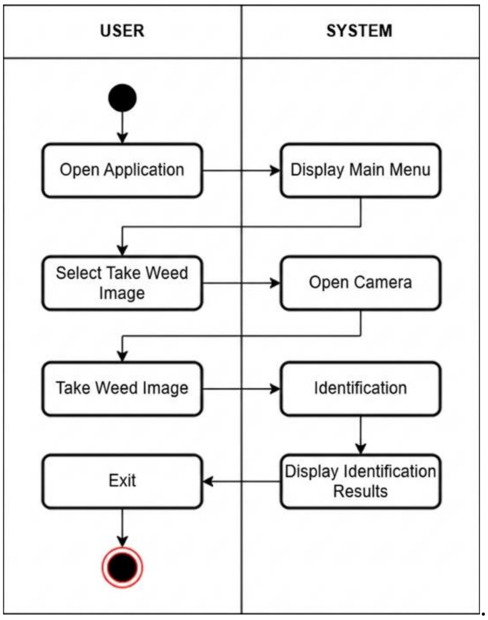

Figure 4. Activity Diagram for Capturing Photos (Camera)

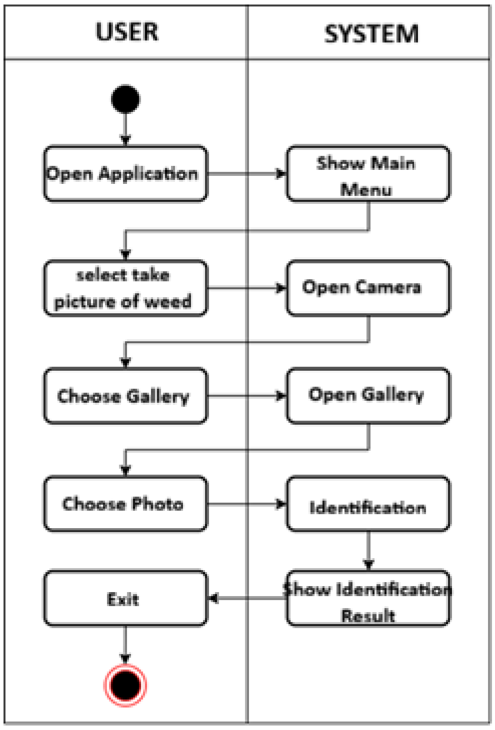

Figure 5. Activity Diagram for Selecting Photos (Gallery)

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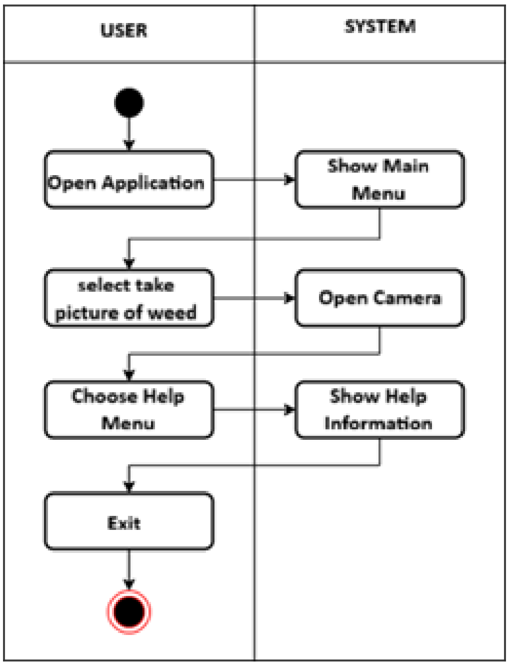

Figure 6. Activity Diagram for Viewing Help

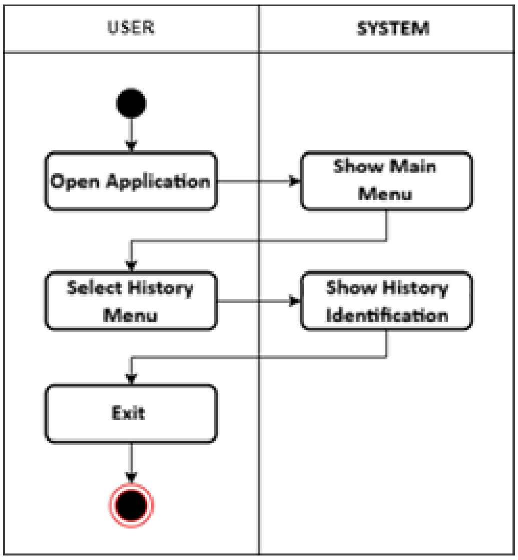

Figure 7. Activity Diagram for Viewing History

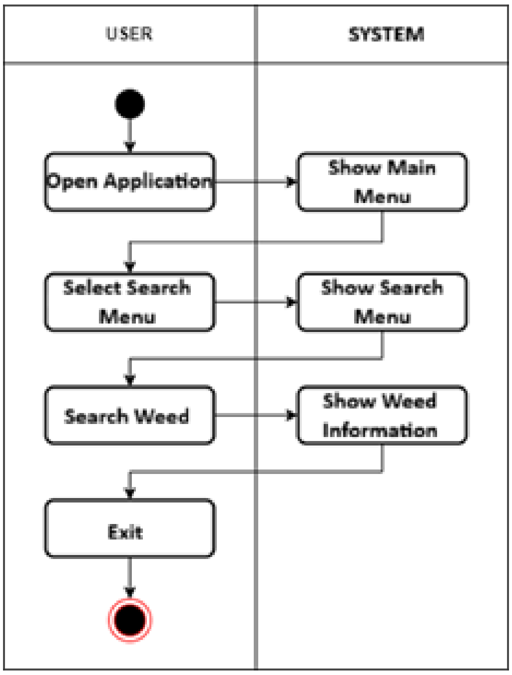

Figure 8. Activity Diagram for Weed Search

4. Result and Discussion

The following section presents the results and discussion of the conducted study, including system testing and analysis of the obtained outcomes. Through this discussion, it can be evaluated whether the developed system successfully achieves the intended objectives and provides the expected benefits based on the prior analysis and system design.

4.1 Model Training Results

In this study, the model was trained for a maximum of 20 epochs; however, the training process was terminated early using the EarlyStopping technique. Early stopping was monitored based on the val_accuracy metric with a patience parameter of 5 and the restore_best_weights option set to True. This configuration means that training was stopped if the validation accuracy did not improve for five consecutive epochs, and the model weights were restored to those corresponding to the best validation performance achieved during training.

At the initial stage of training, a significant improvement in accuracy is observed. At epoch 1, the training accuracy is approximately 0.6573, while the validation accuracy reaches around 0.8729. As the number of epochs increases, both training and validation accuracies continue to improve. At epoch 12, the validation accuracy attains its highest value of

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approximately 0.9875, indicating that the model achieves its optimal performance and is able to learn the underlying patterns effectively. As shown in the table, the training process stops at epoch 17. Although training continues until epoch 17, the validation accuracy does not surpass the peak value achieved at epoch 12. Therefore, the model selected for evaluation is the one obtained at epoch 12 with a validation accuracy of 0.9875. The application of the EarlyStopping technique ensures that the model does not suffer from overfitting.

Table 2. Model Training Results

Epoch	Training		Validation	
	loss	**accu**	**val_loss**	**val_accu**
1	1.1136	0.6573	0.4792	0.8729
2	0.3381	0.9017	0.2889	0.9083
3	0.2046	0.9405	0.1899	0.9479
4	0.1837	0.9459	0.1658	0.9563
5	0.1183	0.9657	0.2162	0.9312
6	0.1423	0.9531	0.1523	0.9479
7	0.0955	0.9729	0.1287	0.9625
8	0.0700	0.9865	0.1167	0.9646
9	0.0752	0.9784	0.0867	0.9771
10	0.0731	0.9729	0.0818	0.9750
11	0.0741	0.9757	0.0906	0.9625
12	**0.0726**	**0.9820**	**0.0547**	**0.9875**
13	0.0775	0.9729	0.0930	0.9708
14	0.0689	0.9793	0.0800	0.9667
15	0.0480	0.9847	0.0593	0.9833
16	0.0479	0.9883	0.0710	0.9750
17	0.0513	0.9838	0.1063	0.9708

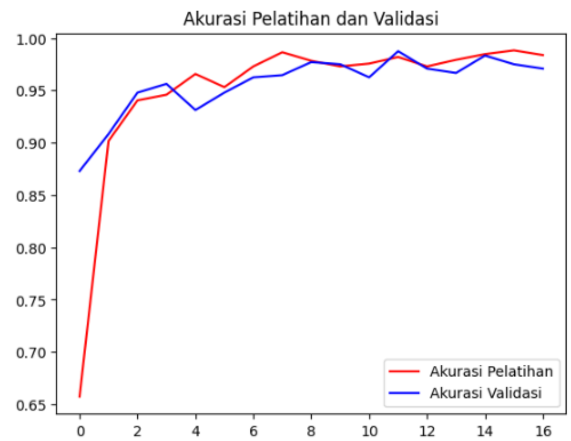

Figure 9. Training Results Graph

The Fig. 7 illustrates the progression of training accuracy and validation accuracy during the model training process. The horizontal axis (x-axis) represents the number of epochs, while the vertical axis (y-axis) denotes the accuracy values. The red line indicates the training accuracy, whereas the blue line represents the validation accuracy.

4.2 Model Evaluation

After the training process is completed, the model is evaluated to measure its performance in classifying weed images and to determine the overall accuracy of the model.

```
16/16 - 24s - loss: 0.0897 - accuracy: 0.9611 - 24s/epoch - 2s/step

Test accuracy: 0.9611452221870422
16/16 [==============================] - 18s 1s/step
```

Figure 10. Evaluation Results

The best validation accuracy achieved during training was 98.75% at epoch 12. However, when evaluated on the independent testing dataset, the model achieved an overall classification accuracy of 96.11%, indicating strong generalization performance.

4.3 Model Testing

In this study, a Confusion Matrix is used to evaluate the performance of the trained CNN model. The Confusion Matrix is a commonly used evaluation technique for assessing the classification performance of a trained model.

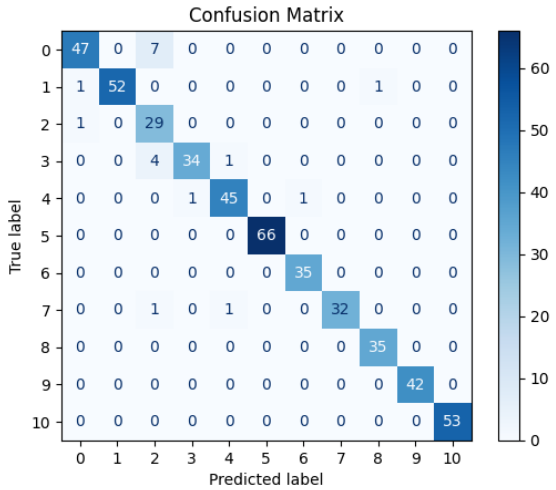

Figure 11. Confusion Matrix Graph

A Confusion Matrix is an N×N matrix, where N represents the number of classes. In the graph shown above, there are 11 classes, represented by labels 0 through 10. The Confusion Matrix includes four key evaluation metrics. First, True Positives (TP) are the diagonal values (from the top-left to the bottom-right)

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that indicate the number of correctly classified samples for each class. Second, False Positives (FP) are the off-diagonal values in the columns corresponding to each class, representing samples incorrectly predicted as that class when they do not belong to it. Third, False Negatives (FN) are the off-diagonal values in the rows corresponding to each class, indicating samples that belong to a class but are incorrectly classified as another class. Finally, True Negatives (TN) are the remaining off-diagonal values that do not fall within the same row or column, representing samples correctly identified as not belonging to a given class.

Table 3. Classification report

Weed Class	Precision	Recall	F1-Score	Support
Alternanthera Philoxeroides	0.96	0.87	0.91	54
Ludwigia Octovalvis	1.00	0.96	0.98	54
Commelina Diffusa	0.71	0.97	0.82	30
Ipomoea Aquatica	0.97	0.87	0.92	39
Euphorbia	0.96	0.96	0.96	47
Pistia Stratiotes	1.00	1.00	1.00	66
Acalyphia Indica	0.97	1.00	0.99	35
Cleome Rutidosperma	1.00	0.94	0.97	34
Mimosa Pudica	0.97	1.00	0.99	35
Eleusine Indica	1.00	1.00	1.00	42
No Weed	1.00	1.00	1.00	53

The table 3 presents several metrics used to evaluate the performance of the model. *Precision* represents the proportion of true positive predictions among all positive predictions. A high precision value indicates that the model rarely produces false positive results. Precision is calculated as $\mathrm{TP}/(\mathrm{TP}+\mathrm{FP})$. *Recall* represents the proportion of true positive predictions among all actual positive samples. A high recall value indicates that the model successfully captures most of the relevant positive instances. Recall is calculated as $\mathrm{TP}/(\mathrm{TP}+\mathrm{FN})$. The *F1-score* is the harmonic mean of precision and recall, providing a balanced measure between the two metrics. It is computed as $2 \times (\mathrm{Precision} \times \mathrm{Recall})/(\mathrm{Precision}+\mathrm{Recall})$. *Support* indicates the number of actual occurrences of each class in the dataset, helping to describe the class distribution.

In addition to evaluating the CNN classification performance using a Confusion Matrix and classification report, an additional experiment was conducted to measure the accuracy of the herbicide recommendation system based on the Cosine Similarity method.

To evaluate the effectiveness of the herbicide recommendation mechanism, a testing procedure was conducted as follows:

1. A subset of 100 test cases was selected from the testing dataset.
2. For each case, the weed species was first identified using the trained CNN model.
3. The identified weed species (single or multiple) were transformed into TF–IDF vectors.
4. Each herbicide description in the database was also converted into a TF–IDF vector.
5. Cosine Similarity was computed between the weed vector and each herbicide vector.
6. The herbicide with the highest similarity score was selected as the recommendation.
7. The recommended herbicide was compared against expert-validated herbicide suitability based on the Registered Agricultural and Forestry Pesticides handbook.

The recommendation result was categorized as:

- **Correct Recommendation (CR)**: The recommended herbicide matches expert-approved herbicide for the identified weed species.
- **Incorrect Recommendation (IR)**: The recommended herbicide does not match expert-approved herbicide.

The recommendation accuracy is calculated as:

$$RA = \frac{CR}{N}\ x\ 100\%$$

where

RA denotes the recommendation accuracy (in percent),

CR represents the number of correct recommendations, and

N is the total number of test cases.

From 100 test cases:

Correct Recommendations (CR): 92

Incorrect Recommendations (IR): 8

Thus,

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$$RA = \frac{92}{100} \times 100\% = 92\%$$

This result indicates that the Cosine Similarity–based recommendation mechanism achieves a **92% accuracy rate**, demonstrating strong capability in matching identified weed species with appropriate herbicide descriptions.

The findings confirm that integrating TF–IDF and Cosine Similarity provides a reliable similarity-based decision mechanism for herbicide selection within a mobile decision-support system.

4.4 Herbicide Recommendation Computation

In this study, the scientific names of weeds and herbicide descriptions are treated as textual data and compared using the Cosine Similarity method. First, the text is transformed into vector representations using the Term Frequency–Inverse Document Frequency (TF–IDF) approach. The following terms are extracted as features, for example, from the description of *Herbicide A*:

$$\begin{bmatrix} \text{“herbicide”, “systemic”, “for”, “controlling”,} \\ \text{“weed”, “Alternanthera”, “Philoxeroides”,} \\ \text{“Commelina”, “Diffusa”, “Eleusine”,} \\ \text{“Indica”, “Ludwigia”, “Octovalvis”} \end{bmatrix}$$

Next, vectors are generated for each weed's scientific name. For instance:

- *Alternanthera philoxeroides*: [0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0]
- *Commelina diffusa*: [0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0]
- *Eleusine indica*: [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0]

The combined vector representation of the three weeds is then expressed as:

[0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0]

This vector is subsequently used in the cosine similarity calculation to determine the most appropriate herbicide recommendation.

Cosine similarity is used to measure the similarity between the herbicide description vector and the weed vector. It is formally defined as:

$$(\mathbf{H}, \mathbf{W}) = \frac{\mathbf{H} \cdot \mathbf{W}}{\| \mathbf{H} \| \ \| \mathbf{W} \|} \tag{1}$$

where the dot product of vectors **H** and **W** is given by:

$$\mathbf{H} \cdot \mathbf{W} = \sum_{i=1}^{n} H_i W_i \tag{2}$$

and the Euclidean norm of a vector is defined as:

$$\| \mathbf{H} \| = \sqrt{\sum_{i=1}^{n} H_i^2}, \| \mathbf{W} \| = \sqrt{\sum_{i=1}^{n} W_i^2} \tag{3}$$

Assume the herbicide description is represented by a simplified TF–IDF vector **H**:

$$\mathbf{H} = [0,0,0,0,0,1,1,1,1,1,1,1,1]$$

The combined vector of the identified weed species (*Alternanthera philoxeroides*, *Commelina diffusa*, and *Eleusine indica*) is represented as vector **W**:

$$\mathbf{W} = [0,0,0,0,0,1,1,1,1,1,1,0,0]$$

Dot Product Calculation:

$$\mathbf{H} \cdot \mathbf{W} = \sum_{i=1}^{13} H_i W_i = 6$$

Vector Magnitude Calculation:

$$\| \mathbf{H} \| = \sqrt{8}$$
$$\| \mathbf{W} \| = \sqrt{6}$$

Cosine Similarity Result:

$$\text{Cosine Similarity} = \frac{6}{\sqrt{8} \times \sqrt{6}} = \frac{6}{\sqrt{48}} \approx 0.866$$

A cosine similarity value of **0.866** indicates a strong correspondence between the herbicide description and the identified weed species. Consequently, *Herbicide A* is considered highly suitable and is selected as the recommended herbicide for weed control.

4.5 System Implementation

The development of the Android-based Weed Identification application includes the following interface components:

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4.5.1 Main Menu Interface

This interface displays the application name and logo, along with several functional buttons, including Capture Image to access the camera, Weed Search, Identification History, About Application, and Exit.

Figure 12. Main Menu Interface

4.5.2 Camera Interface

After the Capture Image button on the main menu is selected, the camera interface is displayed. The camera is used to directly identify weeds, providing two identification modes.

Figure. 13. Camera Interface

4.5.3 Help Interface

The help interface is designed to provide guidance on how to correctly capture weed images. Several indicators are included, such as blurred image, image captured too close, image captured too far, low-light image, and correct image indicators.

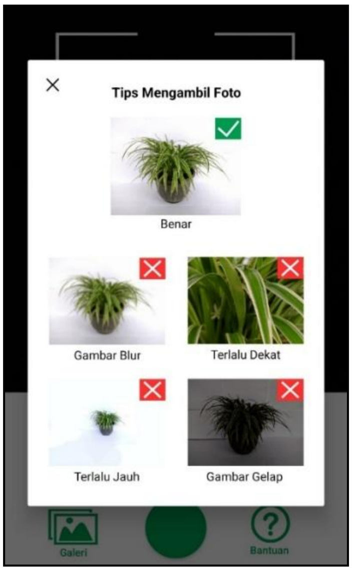

Figure 14. Help interface

4.5.4 Gallery Interface

Similar to the camera interface, the gallery interface is used to identify weeds; however, the identification process is performed by selecting images from the device gallery.

Figure 15. Galery Interface

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4.5.5 Single Identification Result Interface

In the single identification mode, the result interface displays the weed image, its description, and the recommended herbicide for the identified weed.

Figure 16. Single Identification Result Interface

4.5.6 Multiple Identification Result Interface

In the multiple identification mode, the system operates by temporarily storing the first captured image in memory until the third image is acquired, after which the application automatically displays the identification results for all three weeds. This interface also provides a Herbicide Recommendation button that allows users to view suitable herbicides based on the cultivated crop.

Figure 17. Multiple Identification Result Interface

4.5.7 No-Weed Detection Interface

When no weed is detected, the No Weed Detected interface is displayed. This interface appears when the input image does not contain weed objects or consists of random images.

Figure 18. No-Weed Detection Interface

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4.5.8 Herbicide Recommendation Interface

This interface presents herbicide recommendations for rice cultivation based on the three previously identified weed species. The recommended herbicide is selected as the one with the highest similarity score to the identified weeds. The displayed information includes the herbicide name, active ingredients, and a brief description of the herbicide.

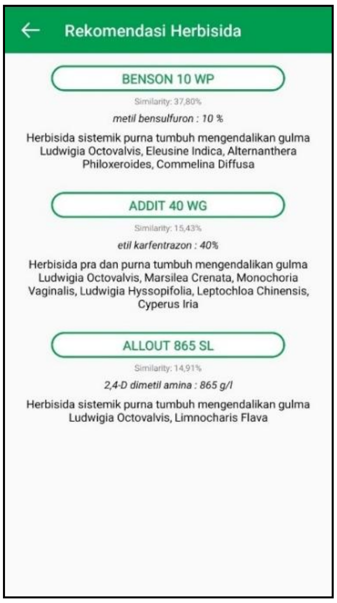

Figure 19. Herbicide Recommendation Interface

4.5.9 Weed Search Interface

This interface is used to directly search for weed information by entering the weed name.

Figure 20. Weed Search Interface

4.5.10 Identification History Interface

In this interface, each completed weed identification—whether obtained from the camera or the gallery—is stored and displayed as an item in the identification history.

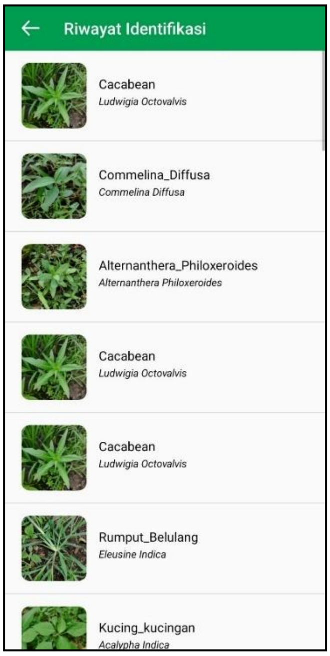

Figure 21. Identification History Interface

5. Conclusion

This study successfully designed and implemented an Android-based weed identification and herbicide recommendation system using a Convolutional Neural Network. A MobileNetV2-based CNN model achieved a best validation accuracy of 98.75% and a testing accuracy of 96.11%, demonstrating strong performance and suitability for mobile deployment. Integration with TensorFlow Lite enables efficient on-device weed identification through a smartphone camera, while the Cosine Similarity method effectively matches identified weed species with appropriate herbicides. The proposed application provides an accurate, efficient, and practical decision-support tool for field-level weed management.

Conflicts of Interest

The authors declare that there are no conflicts of interest related to this study.

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Author Contributions

Conceptualization, Ahmad Izzuddin and Ryan Prayuga Ardiansyah; methodology, Ahmad Izzuddin; software, Ahmad Izzuddin; validation, Ahmad Izzuddin, Ryan Prayuga Ardiansyah, and Andrik Sunyoto; formal analysis, Ahmad Izzuddin; investigation, Ahmad Izzuddin and Dyah Ariyanti; resources, Andrik Sunyoto; data curation, Ahmad Izzuddin; writing—original draft preparation, Ahmad Izzuddin; writing—review and editing, Ryan Prayuga Ardiansyah, Dyah Ariyanti, and Ira Aprilia; visualization, Ahmad Izzuddin; supervision, Andrik Sunyoto; project administration, Dyah Ariyanti; funding acquisition, Ira Aprilia.

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