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AI-Driven mobile application in Sinhala for weed identification and herbicide recommendation

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Abstract

Weed infestation poses a significant challenge for paddy farmers in Sri Lanka, since it reduces crop yield, degrades quality, and increases production costs. Despite the availability of many applications for weed detection and management, they are quite expensive, not real-time, and limited to English-language users. To address these research gaps, this research proposes a real-time weed identification and herbicide recommendation system for farmers in the Sinhala language. This research presents a mobile application integrated with an image-based deep learning model that detects and classifies the captured weeds, and then recommends suitable herbicides in Sinhala. Deep learning models, including Simple Convolutional Neural Network (SimpleCNN), MobileNetV2, and EfficientNetB0, were trained using a locally captured dataset of common weeds such as *Crassula aquatica, Micranthemum*, and *Scurvy,* commonly found in Sri Lankan paddy fields. The primary dataset consisted of 300 images measuring 256×256 pixels for each of the three classes, which were captured, preprocessed, augmented and annotated to avoid overfitting and ensure class balance. For a fair comparison, all three models were trained with a batch size of 32, an initial learning rate of 0.001, 8 epochs, 0.05 label smoothing and with Adam optimizer. Among these, EfficientNetB0 outperformed the others, achieving 97.53% accuracy, 0.97 precision, 0.975 recall and 0.977 F1-score. The final model was converted to .tflite format and integrated into a Flutter-based mobile application. In addition, a secondary dataset on herbicides was obtained from online sources, and its credibility was verified by a local agricultural advisor. The developed mobile application provides users with weed identification results and herbicide recommendations in Sinhala. A qualitative usability evaluation of the mobile application was conducted with eight local farmers with moderate knowledge of smartphones, using a purposive sampling technique. Insights from farmers indicated that this system is a promising, cost-effective alternative for weed detection and management. This study contributes to enhancing sustainable agriculture through AI-assisted weed detection and localized herbicide recommendations.

Keywords: EfficientNetB0, Flutter Application, Sinhala Language, Weed Detection, Herbicide Recommendation

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Introduction

Agriculture plays a vital role in the Sri Lankan economy, where paddy cultivation serves as the primary livelihood for the majority of the rural population. Paddy cultivation, commonly referred to as rice cultivation, holds a prominent place in Sri Lanka, with a history of over 2,500 years. Over the centuries, paddy farming has served as a foundation for food security while substantially contributing to the country's economic development. The statistics show that paddy farming occupied nearly 29% of Sri Lanka’s total agricultural land, covering approximately 818,000 hectares and producing around 3.5 million metric tons of rice in 2020. In the same year, the agricultural sector, especially paddy cultivation, contributed approximately 7.7% of Sri Lanka's Gross Domestic Product (Dadashzadeh et al., 2020). However, the presence of weeds in paddy fields poses a major challenge in modern agriculture, particularly in resource-constrained farming communities such as Sri Lanka. Weeds affect both the yield and quality of the crops, leading to economic loss for farmers (Gao et al., 2018). The global estimate of the reduction in crop production by weeds is nearly 30% (Gao et al., 2018). In many agricultural contexts, the weed identification and herbicide application practices are predominantly conducted manually, which often results in inefficiency, increased labor costs, delays in crop production and inaccurate herbicide usage. Despite the clear advantage of site-specific targeted herbicide usage, including the reduction of herbicide usage by 40–60%, the manual spraying is still widely practiced mainly due to the lack of efficient, usable and accessible technologies (Nikolić et al., 2021). In summary, weeds increase production costs to a greater extent while also harming the environment through the overuse of chemical substances.

With advances in Artificial Intelligence (AI), especially in computer vision, modern solutions have been developed to automate agricultural processes and enhance precision in field management. Several studies have explored the potential of AI for weed detection and management systems in agricultural settings, employing a range of deep learning architectures and sensing technologies (Jin et al., 2022a). For instance, Yu et al. (2019) employed several deep convolutional networks for weed detection, with VGGNet outperforming the other models in precision, F1-score, and recall in the study, including DetectNet, AlexNet, and GoogleNet. In another work, a crop-weed classification system based on VGG16 demonstrated higher accuracy than other traditional machine learning approaches (G C et al., 2022). The comparative analysis of VGG16 Convolutional Neural Networks (CNNs) with traditional machine learning algorithms such as Support Vector Machines (SVMs) in controlled greenhouse environments achieved F1-scores of up to 100% in crop classification tasks. Since the system was only tested in greenhouse settings with controlled lighting and simplified backgrounds, the results could not be generalized as they may not represent complex real-world field conditions. Similarly, Jin et al. (2022b) proposed a novel deep learning-based method for weed detection in vegetable crops using CNN, where the model was found to be robust with a precision of 98.7%, recall of 98.2%, and F1-score of 98.4% under varying lighting conditions. Other deep learning-based weed detection studies include weed detection in lettuce crops using multispectral imagery (Osorio et al., 2020) and weed detection in soybean fields using lightweight models (Razfar et al., 2022). However, the above studies focus only on weed detection and have not incorporated herbicide recommendations, which might greatly increase the adoption of these systems.

A systematic literature review highlighted the use of unmanned aerial vehicles (UAVs) along with machine vision systems and deep learning algorithms as key drivers of modern weed detection and management solutions (Murad et al., 2023). Accordingly, Silva et al. (2024) compared YOLOv8, Mask R-CNN, and U-Net architectures to detect and segment weeds using aerial imageries captured using drones in soybeans and bean fields. The study demonstrated that integrating UAVs with real-time object detection models achieved higher accuracy in identifying weed infestations across larger agricultural areas. YOLOv8 outperformed other models, achieving a precision of 0.99 and an mAP50 of 97%. Similarly, a smart sprayer system with mounted cameras developed using YOLOv4 and deployed on edge computing devices, to trigger targeted spraying, demonstrated that overall chemical usage was reduced by nearly 70% compared to traditional broadcast spraying (Upadhyay et al., 2024). The findings support the claims from Nikolić et al. (2021) and Gerhards et al. (2022) on site-specific herbicide application. While these approaches demonstrated the feasibility of combining drone technology with deep learning for large-scale weed monitoring, the systems focus exclusively on detection and do not provide herbicide recommendations. Additionally, the high costs of drone infrastructure and the technical expertise required pose significant barriers for smallholder farmers in developing agricultural regions, as highlighted by Murad et al. (2023).

With particular reference to the Sri Lankan context, research on the application of artificial intelligence for weed management remains limited. The study by Warnakulasooriya et al. (2024), which developed an autonomous paddy weed detection and removal system using computer vision and deep learning techniques, is promising in this regard. The study demonstrated the potential of applying artificial intelligence for weed identification and automated weed management in Sri Lankan paddy farms. However, the proposed system primarily focused on weed detection and removal and did not incorporate herbicide recommendation functionality, mobile-based deployment, or localized language support for farmer interaction that might improve the usability of the intended system.

In addition to the research listed above, several agricultural applications have been developed over time to support local farmers. The "Krushi Advisor" application, developed by the Department of Agriculture, provides information on crop management, pest control, and fertilizer application localized in both Sinhala and Tamil languages (Department of Agriculture, Sri Lanka, 2021). Similarly, the “SL Paddy Fertilizer” applications provide fertilizer recommendations based on the inputs such as crop stage, soil conditions, and other user-input parameters (Department of Agriculture, Sri Lanka, 2025). The above applications provide general information and fertilizer recommendations, respectively, but do not support real-time problem diagnosis or site-specific recommendations. Furthermore, the "Govi Mithuru" application also provides personalized agricultural advisory services through chat-based and voice-assisted interactions in local languages, but the real-time image-based weed identification or targeted herbicides recommendation is not available either (Wijayakumara, 2019).

The literature review indicates that, despite the availability of several agricultural decision-support systems in Sri Lanka, a significant research gap remains. The available systems have few required functionalities, but the focus on real time weed identification and herbicide recommendation is comparatively sparse. In addition, there are issues related to the usability and accessibility of such applications to the Sri Lankan local farmers, as they primarily support English. The proposed study seeks to address this gap by developing an AI-driven mobile application for weed identification and herbicide recommendations, specifically designed for Sri Lankan paddy farmers, thereby improving accessibility, supporting informed decision-making, and promoting sustainable weed management practices. Through this, the study also seeks to contribute to achieving Sustainable Development Goal (SDG) 2: Zero Hunger. It aims to enhance agricultural productivity and reduce crop losses from weed infestations, while supporting sustainable food production systems through the adoption of precision agriculture technologies.

Methodology

This study presents the development of a deep learning-based weed identification and herbicide recommendation system specifically designed for paddy cultivation in Sri Lanka. The system addresses critical gaps in current weed management practices by integrating deep learning-based image classification with a Sinhala language interface. This would enhance accessibility and usability for local farmers. Unlike existing solutions that require manual weed identification and constant internet access, the proposed application aims to operate offline while providing real-time weed identification. The overall research methodology is shown in Figure 1.

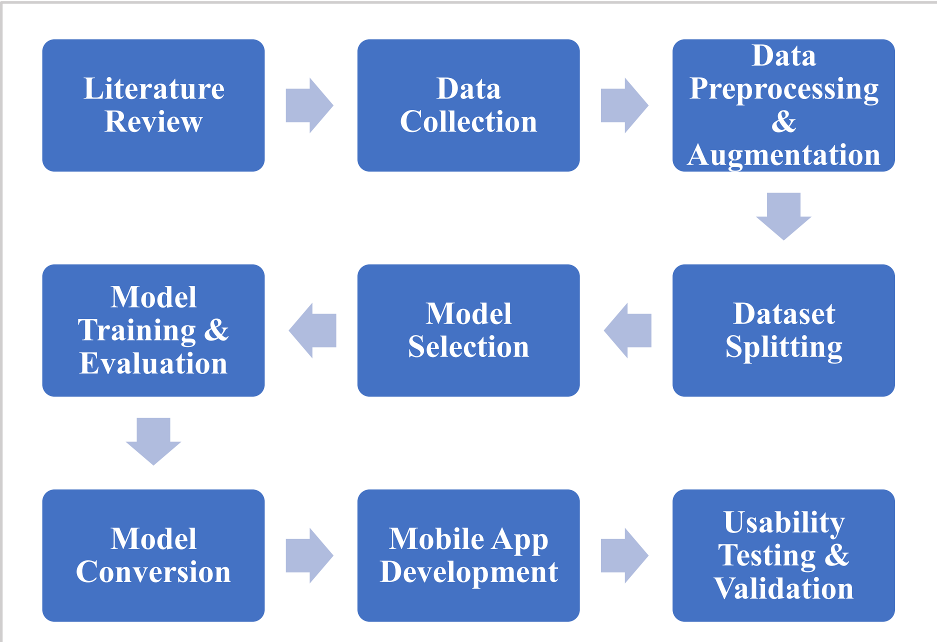

Figure 1. Schematic diagram of the methodology applied in the present study

Data collection

The primary image dataset was collected directly from paddy fields in Sri Lanka under various lighting conditions from multiple angles and positions to ensure dataset diversity. The dataset consisted of three locally prevalent weed species: *Crassula aquatica* (දියමිත්ත), *Micranthemum* (බෙරමැටි), and Scurvy weed (දියමෙමෙඩිරිය) as in Figure 2, with 300 images from each class. Sinhala common names and local terminologies were also included in the dataset in consultation with local farmers to ensure cultural appropriateness and practical relevance of the proposed application. Besides the primary image data, secondary data related to herbicide information comprising the chemical names, active ingredients, target weed species, application timing, and dosage were collected from established online agricultural resources and verified by a local agricultural advisor.

Figure 2. Representative images from Weed Classes (from left to right): *Crassula aquatica* (දියමිත්ත), *Micranthemum* (බෙරමැටි), and Scurvy weed (දියමෙඬේරිය)

Data preprocessing and splitting

The obtained dataset was preprocessed as the raw image data exhibited inconsistencies in size, resolution, lighting conditions, and image quality. The preprocessing involved categorizing images by weed species, removing low-quality samples, rescaling to standard dimensions, and applying accurate class labels. The dataset was partitioned using a stratified shuffle-splitting approach based on individual image samples. Each image was treated as an independent sample during the partitioning process. Prior to splitting, duplicate and corrupted images were removed, resulting in a final dataset of 808 images. The dataset was then divided into 646 training images (80%), 81 validation images (10%), and 81 testing images (10%). Stratified sampling was employed to preserve the representation of all three weed classes (*C. aquatica*, *Micranthemum*, and Scurvy weed) across the training, validation, and testing subsets. A fixed random seed (SEED = 42) was used to ensure reproducibility of the data partitioning process. Additionally, the data on the herbicides provided the basis for the herbicide recommendation module integrated within the application.

Model training

Model development environment preparation

Model training was conducted using Google Colab with NVIDIA GPU acceleration, utilizing the TensorFlow framework and Keras API. This cloud-based environment provided the computational resources required to train deep learning models effectively without the need for dedicated hardware infrastructure.

Hyperparameter optimization and data preparation

To ensure reproducibility and enable fair comparative analysis across all evaluated architectures, hyperparameters were selected through manual empirical tuning. Hyperparameters were selected through manual empirical tuning based on preliminary experiments and commonly adopted values reported in previous deep learning studies. Several combinations of learning rate, batch size, dropout rate, and label smoothing were evaluated before selecting the final configuration. Consequently, all models were trained using an input image size of 256×256 pixels, a batch size of 32, and the Adam optimizer with an initial learning rate set at 0.001. Categorical cross-entropy served as the loss function, and a label smoothing value of 0.05 was incorporated to reduce overconfidence and improve generalization. Fine-tuning was performed at a reduced learning rate of 0.0001 to enable gradual adjustment of pre-trained weights, and all models were trained for 8 epochs with a fixed random seed to maintain experimental consistency.

To improve model generalization and reduce overfitting, online data augmentation was applied exclusively to the training dataset using the TensorFlow data pipeline. During each training iteration, augmented images were generated dynamically rather than being permanently stored as additional image files. The augmentation techniques included random horizontal and vertical flipping, random brightness adjustment (±20%), random contrast variation (0.85–1.15), random saturation adjustment (0.85–1.15), random hue adjustment (0.02), and random cropping followed by resizing back to 256 × 256 pixels. The validation and testing datasets were intentionally kept unchanged to ensure an unbiased evaluation of model performance. Since augmentation was performed online, the physical size of the dataset remained unchanged, and no separate augmented dataset was generated. Instead, different augmented versions of the training images were created dynamically during each training epoch, exposing the model to diverse image variations while maintaining the original dataset size. Additionally, to address the class imbalance among weed species after removing low-quality images, class weights were computed automatically using the balanced weighting strategy available in Scikit-learn. This approach assigned proportionally higher weights to underrepresented classes, ensuring that the model trained with equal emphasis across all weed species without bias toward the most frequently occurring class.

Model architectures and training process

Three CNN architectures, namely SimpleCNN, MobileNetV2, and EfficientNetB0, were evaluated. The SimpleCNN is a lightweight custom baseline architecture trained from scratch, comprising three convolutional blocks with 3×3 kernels, max pooling, global average pooling, and 40% dropout for regularization. Secondly, MobileNetV2 is a pre-trained lightweight architecture employing depth-wise separable convolutions and inverted residual blocks, offering reduced training time and suitability for mobile deployment. EfficientNetB0, a state-of-the-art architecture, utilizes compound scaling to jointly optimize network depth, width, and resolution, while providing robust transfer learning capabilities and advanced feature representation.

The SimpleCNN was trained in a single phase, whereas MobileNetV2 and EfficientNetB0 were trained using a two-phase transfer learning approach. Phase 1 involved training only the newly added classification layers while the pre-trained base layers remained frozen (8 epochs, learning rate 0.001), and phase 2 involved fine-tuning all unfrozen layers with a reduced learning rate of 0.0001 to adapt pre-trained features to weed-specific classification patterns.

Model evaluation

Each of the trained models was evaluated on an independent test set using accuracy, precision, recall, and F1-score. Visualization techniques, namely confusion matrices, ROC curves, and per-class F1-score plots, were generated to provide a comprehensive assessment of model performance. The best-performing model, selected based on validation accuracy, was subsequently exported in TensorFlow Lite (TFLite) format for integration into the mobile application.

Mobile application development

The mobile application interface was designed in Figma, with an emphasis on simplicity, accessibility, and usability, incorporating Sinhala throughout all screens. The application comprised a splash screen, home screen, camera screen, gallery screen, and prediction results screen. The application was developed using Flutter and Dart, enabling cross-platform compatibility and consistent performance across both Android and iOS devices. The trained deep learning model was converted to the TensorFlow Lite format and integrated into the application using the TFLite Flutter plugin, enabling fully on-device inference without requiring internet connectivity. This demonstrates the practical feasibility of on-device weed identification and herbicide recommendation. The deployed application was successfully evaluated through usability testing with local paddy farmers. However, the present study primarily focused on classification performance and functional validation rather than detailed computational benchmarking. The mobile application works as follows: When a user captures or uploads an image, the input is preprocessed and passed to the embedded TFLite model for inference. After this, the prediction results are displayed, along with comprehensive herbicide recommendations in Sinhala. The application was also tested using different device configurations to verify stability, classification accuracy, and usability under varied hardware conditions.

Usability testing

Using purposive sampling, eight paddy farmers representing the target users with limited smartphone use were selected. Participants were allowed to interact with the prototype after a brief introduction. They were asked to accomplish predefined tasks, and their interactions were recorded. Following the interaction, the participants were brought together for a discussion to gather feedback on the system's usability, usefulness, language accessibility, and areas for improvement. The findings were based on participant observations and feedback rather than formal quantitative analysis.

Results

This section presents the performance analysis of the three deep learning architectures, namely SimpleCNN, MobileNetV2, and EfficientNetB0, evaluated for weed classification in Sri Lankan paddy fields. Each model was trained and tested on a labelled dataset comprising three weeds: *C. aquatica, Micranthemum,* and Scurvy Weed.

Training and validation accuracy analysis

Training and validation accuracy curves were examined for each model to assess learning behavior and generalization capability (Figure 3).

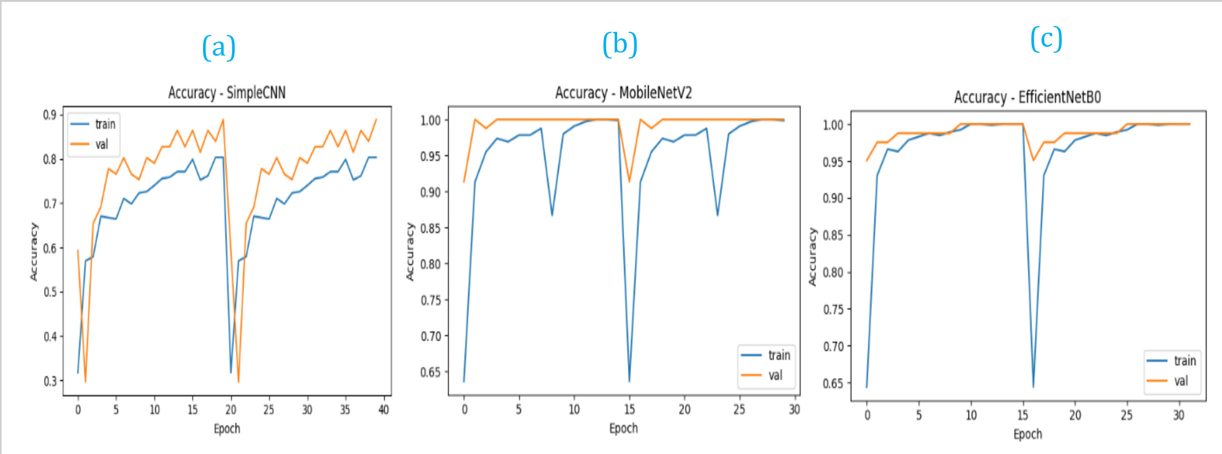

Figure 3. Training and validation accuracy curves of (a) SimpleCNN, (b) MobileNetV2, and (c) EfficientNetB0

As shown in Figure 3(a), the SimpleCNN model exhibited a gradual increase in both training and validation accuracy during the initial epochs. Although the model learns meaningful feature representations, the gap between the training and validation curves remains noticeable towards the end of training, indicating limited generalization capability. The relatively slower convergence reflects the inherent limitations of training a lightweight custom architecture from scratch, without the benefit of pre-learned feature representations, resulting in lower final validation accuracy (83.95%) compared to the other models.

MobileNetV2 demonstrated considerably faster and smoother convergence than SimpleCNN (Figure 3(b)). Both training and validation accuracy increased rapidly in the first few epochs, surpassing 90% early in training and ultimately reaching 96.30% validation accuracy. The close alignment between the two curves throughout training indicates strong generalization capability and minimal overfitting, suggesting that the model successfully captured discriminative features across all three weed classes. This improved convergence may be primarily due to the transfer learning strategy and the efficient depth-wise separable convolution architecture employed by MobileNetV2, which enables the model to achieve a validation accuracy of 96.30%.

EfficientNetB0 outperformed both architectures with the highest validation accuracy of 97.53% and exhibited the most stable learning behavior. The training and validation accuracy curves converged almost completely following the initial epochs, demonstrating exceptional stability and generalization (Figure 3(c)). This near-perfect alignment, smooth convergence and high accuracy affirm that EfficientNetB0's compound scaling mechanism effectively balances network depth, width, and resolution, enabling robust feature learning with minimal overfitting.

It is noted that there were temporary fluctuations in the training and validation accuracy curves during training, particularly for the transfer learning models (Figure 3(b) and 3(c)). These fluctuations are primarily associated with the transition from the feature extraction stage to the fine-tuning stage. During the initial stage, only the newly added classification layers were trained while the pre-trained layers remained frozen. In the fine-tuning stage, selected pre-trained layers were unfrozen and updated using a lower learning rate, resulting in short-term variations before convergence. Whereas Figure 3(a) (SimpleCNN), which was trained from scratch, exhibits comparatively smoother learning without a transition between training phases. In addition, the relatively small field-collected dataset and the use of online data augmentation might have introduced minor variations in the optimization process. Nevertheless, regularization techniques, including dropout and label smoothing, promoted stable convergence, and all three models ultimately achieved stable validation performance, indicating that the observed fluctuations represent normal optimization behavior rather than model instability.

Collectively, these results confirm that transfer learning-based architectures (MobileNetV2 and EfficientNetB0) converge faster, generalize more effectively, and achieve superior classification accuracy compared to the custom SimpleCNN baseline. The close agreement between the training and validation curves observed for MobileNetV2 and EfficientNetB0 suggests that the adopted data augmentation strategy, label smoothing, and transfer learning effectively minimized overfitting while improving model generalization.

Training and validation loss analysis

Loss curves were analyzed alongside accuracy metrics to provide a comprehensive assessment of each model's learning dynamics.

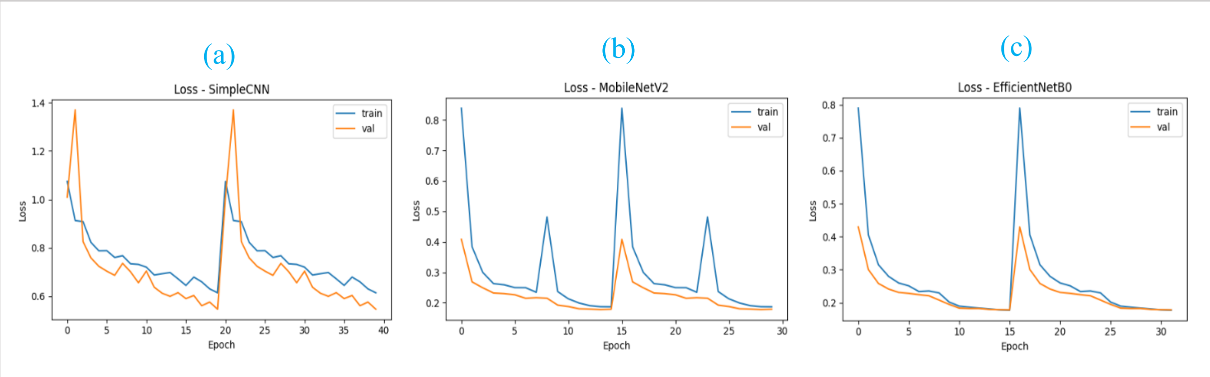

Figure 4. Training and validation loss curves of (a) SimpleCNN, (b) MobileNetV2, and (c) EfficientNetB0

As shown in Figure 4(a), the SimpleCNN model exhibited a gradual decline in training loss; however, validation loss plateaued after several epochs, indicating limited capacity to reduce prediction error on unseen data. This behavior is consistent with the generalization limitations observed in the accuracy analysis. MobileNetV2 displayed smooth and continuously decreasing training and validation loss curves with a minimal gap between them throughout training (Figure 4(b)).

The final loss values were substantially lower than those recorded for SimpleCNN, confirming that MobileNetV2 maintained a consistently low error rate across all weed classes. As shown in Figure 4(c), EfficientNetB0 achieved the lowest loss among the three architectures. Both curves declined sharply in the early epochs and converged near zero in the later stages of training. This trend could be due to the efficient learning of EfficientNetB0 with batch normalization and swish activation functions. The loss analysis curves support the findings on accuracy, since EfficientNetB0 exhibits the best convergence behavior, the lowest final loss, and the greatest stability across all training epochs.

Confusion matrix and classification report analysis

To evaluate classification performance at the individual-class level, confusion matrices and per-class classification reports were generated. The SimpleCNN model exhibited several misclassifications, particularly between *Micranthemum* and Scurvy Weed. This might be due to the model's difficulty in distinguishing morphologically similar weed species. *C. aquatica* was classified with a recall of 93.10%, while overall accuracy reached 83.95% by SimpleCNN (Figure 5).

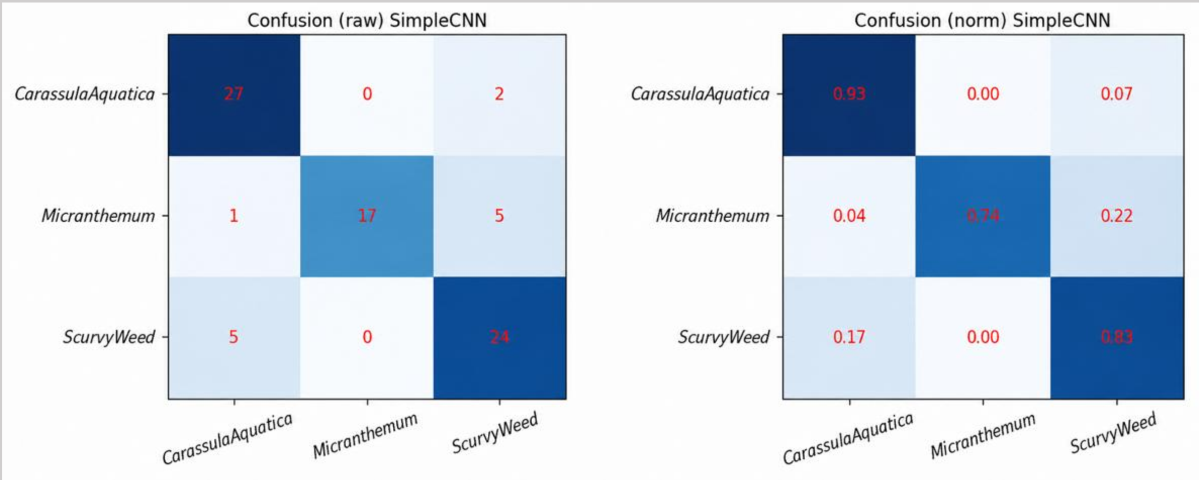

Figure 5. Confusion matrix of SimpleCNN

MobileNetV2 demonstrated a significant improvement compared to SimpleCNN, with only three misclassifications across the entire test set. *Micranthemum* was classified with both 100% precision and recall, and comparable performance was observed for the remaining two classes, yielding an overall accuracy of 96.30%. These results indicate that MobileNetV2's feature extraction layers effectively captured fine-grained weed characteristics (Figure 6).

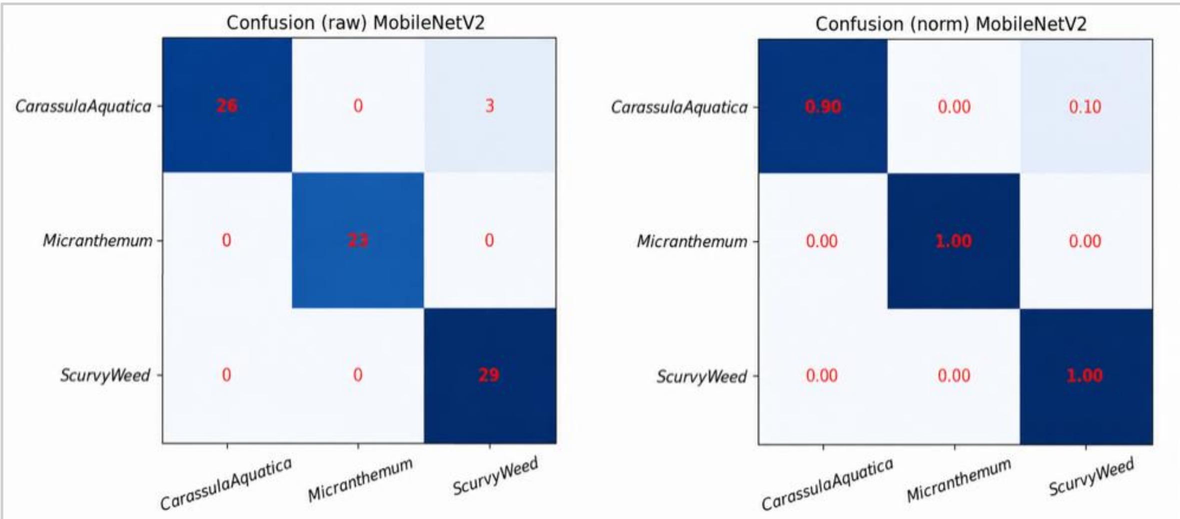

Figure 6. Confusion matrix of MobileNetV2

EfficientNetB0 demonstrated an excellent classification performance, with accurate predictions across all three weed categories and extremely rare misclassifications, producing an overall accuracy of 97.53%. These results confirm its superior capacity to differentiate visually similar weed species under real-world field conditions (Figure 7).

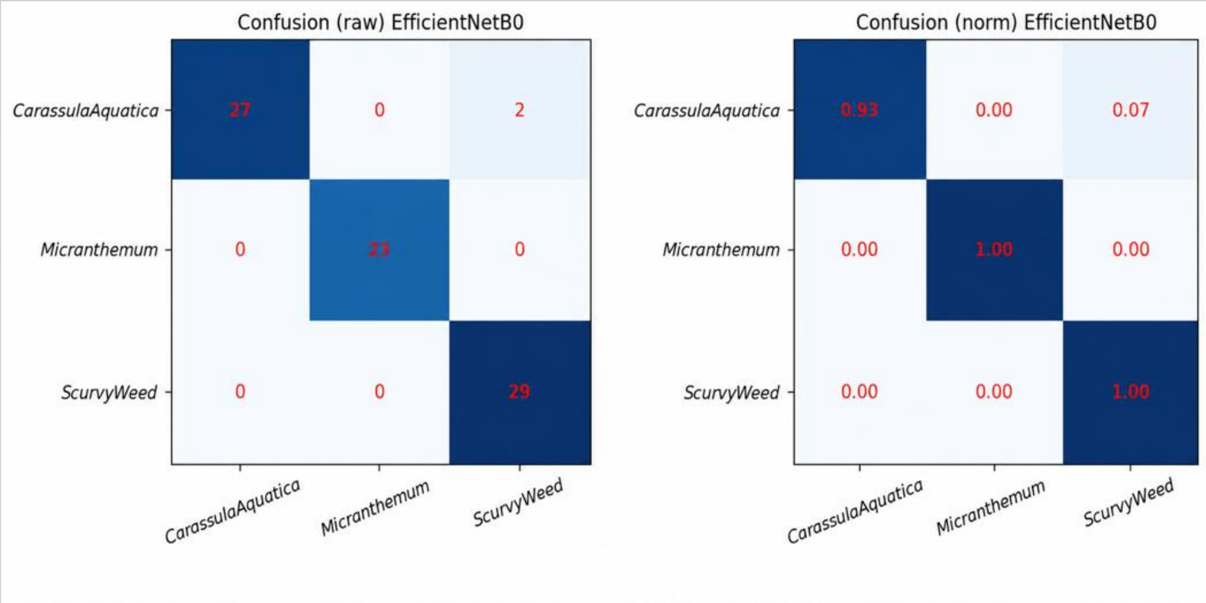

Figure 7. Confusion matrix of EfficientNetB0

Table 1 compares the classification performance of the three models in terms of precision, recall, F1-score, and accuracy. EfficientNetB0 achieved the best overall performance, with the highest values across all evaluation metrics, followed closely by MobileNetV2. SimpleCNN showed comparatively lower performance.

Table 1: Quantitative evaluation of model performance*

Model	Precision	Recall	F1-Score	Accuracy
SimpleCNN	0.854	0.839	0.840	83.95%
MobileNetV2	0.966	0.963	0.963	96.30%
EfficientNetB0	**0.977**	**0.975**	**0.977**	**97.53%**

**Values in bold indicate the highest precision, recall, F1-score, and accuracy among the compared models.*

Mobile application development

The final output screens of the mobile application are presented in Figure 8, illustrating the end-to-end workflow from image capture through to weed identification and recommendation display. In summary, the application was found to be functionally complete, culturally appropriate, and practically accessible for Sri Lankan smallholder paddy farmers.

Figure 8. Final output screens of the mobile application

Usability testing

The qualitative usability evaluation with eight purposively selected paddy farmers produced generally positive feedback on the application. Participants with limited to moderate smartphone experience were able to complete the main tasks, including capturing or uploading weed images, viewing classification results, and accessing herbicide recommendations suggesting the usability of the application. This also suggests that the application workflow was clear and manageable for the intended users with limited to moderate smart experience.

Participants considered the combination of weed identification and herbicide recommendation within a single application useful for field-level decision-making. The Sinhala-language interface was also well received, as users were able to understand the classification results and herbicide guidance without translation assistance. Offline operation was another valued feature, particularly for use in areas with limited or unstable Internet connectivity. Since Internet connectivity may be unreliable in rural agricultural areas, the ability to perform weed identification and access herbicide recommendations without continuous connectivity was considered very useful. Participants also identified areas for further improvement during the group discussion. Overall, the findings suggest that the application was usable, useful, accessible in the local language, and appropriate for field use. Since the evaluation involved only eight participants, the results should be regarded as preliminary and confirmed through a larger usability study.

Discussion

The proposed system offers several practical advantages over previous studies. Unlike many existing solutions that depend on specialized hardware or continuous internet connectivity, the developed application runs entirely on a standard smartphone and can operate offline. The system can provide weed identification and herbicide recommendations in less than five seconds, making it suitable for real-time use in the field. Furthermore, the integration of the Sinhala language makes the application more accessible to Sri Lankan farmers and addresses an important barrier to technology adoption.

Compared with existing local agricultural applications such as Krushi Advisor (Department of Agriculture, Sri Lanka, 2021) and Govi Mithuru (Wijayakumara, 2019), which mainly provide general agricultural information and advisory services, the proposed application introduces image-based weed identification powered by deep learning. In addition, it provides site-specific herbicide recommendations and supports offline operation, offering a more practical solution for day-to-day weed management in paddy cultivation. The final system was evaluated against both functional and non-functional requirements. The results confirmed that all core functionalities operated successfully, including image capture, gallery image loading, weed classification, herbicide recommendation generation, and navigation between application screens. The non-functional evaluation also produced encouraging results. Prediction response times remained below five seconds, Sinhala language support was fully functional, and user feedback from the usability evaluation was overwhelmingly positive, with more than 90% of participants expressing satisfaction with the system. In addition, the application architecture was designed to accommodate future enhancements, including new weed classes and recommendation features.

Despite the promising performance of the proposed system, this study has several limitations. First, the dataset consisted of a relatively small number of field-collected images, which may limit the model's ability to generalize to more diverse environmental conditions and weed variations. Second, the dataset was partitioned using a stratified image-level splitting approach. Although this ensured balanced class distributions, images captured from the same weed plant may have been assigned to different subsets, and therefore, there is a little possibility of data leakage that cannot be completely excluded. Third, the usability evaluation was conducted with only eight paddy farmers, providing preliminary insights into the application's usability and practicality but limiting the generalizability of the findings. Finally, the study focused primarily on classification performance and the feasibility of mobile deployment; comprehensive benchmarking of computational performance, including inference latency, memory usage, and hardware-specific evaluation, was beyond the scope of this work. Future research will address these limitations by expanding the dataset, adopting plant-level or field-level data partitioning, conducting large-scale usability studies with a more diverse group of users, and performing detailed computational performance evaluations on multiple mobile platforms.

Conclusions

Weed management constitutes a critical challenge in Sri Lankan paddy cultivation, with weed infestations estimated to cause yield losses of 50–70% in affected fields. Existing Sri Lankan agricultural applications provide general advisory services in local languages but lack AI-driven visual diagnosis capabilities. Prior to this work, no system existed that combined real-time weed identification with site-specific herbicide recommendations in the Sinhala language through an offline-capable mobile platform.

This study developed a deep learning-based mobile application for paddy weed identification and herbicide recommendation, trained on a dataset of 808 images spanning three common weeds, *C. aquatica, Micranthemum,* and Scurvy Weed. Three deep learning architectures were systematically evaluated, with EfficientNetB0 achieving the highest classification accuracy of 97.53%. The selected model was converted to the TensorFlow Lite format and integrated into a Flutter-based mobile application with complete Sinhala language support and on-device inference, delivering real-time predictions within 5 seconds. A usability evaluation involving eight paddy farmers confirmed that the system is practically usable, culturally accessible, and well-suited to the resource constraints of rural Sri Lankan farming communities. Future work will benefit from expanding the weed species dataset, integrating Tamil-language support, and incorporating GPS-enabled, location-specific recommendations.

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Conflict of interest statement

The authors declare no conflict of interest.

Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contribution

All authors contributed to the conception and design of the study, data collection and analysis, interpretation of the results, and preparation and revision of the manuscript. All authors reviewed and approved the final version of the manuscript.

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