Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ENHANCING WEED CLASSIFICATION IN AGRICULTURE: LEVERAGING DEEP NEURAL NETWORKS AND SEGMENT ANYTHING MODEL

PRASANNA DRL[1] , DIVYA LINGINENI[2], MANISAIGANESH KOTHA[3] , QAWIUDDIN MOHAMMED[4]

[1]Assistant Professor. Vasavi College of Engineering, Department of Information Technology, Telangana, India

[2]Assistant Professor. Vasavi College of Engineering, Department of Information Technology, Telangana, India

[3]Student. Vasavi College of Engineering, Department of Information Technology, Telangana, India

[4]Student. Vasavi College of Engineering, Department of Information Technology, Telangana, India

E-mail: [1]prasannadusi@staff.vce.ac.in ,[2*]Divya.Lingineni@staff.vce.ac.in, [3]kothamanisaiganesh18@gmail.com, [4]uddinmohammed527@gmail.com

ABSTRACT

The paper entails the utilization of deep neural network models such as ResNet50, and Inception V3 with a state-of-the-art segmentation model Segment Anything Model from Facebook for enhancing plant identification. The primary objective is to enhance weed identification within agriculture through the utilization of Deep Neural Networks as well as the Segment Anything Model. The study discusses how enhanced weed species identification accuracy as well as precision through advanced segmentation techniques can be achieved. The study used Segment Anything Masks (SAM) for image augmentation, preprocessing techniques of neural networks, as well as the structure of the neural network for classifying. It further used comparative modeling of models such as DenseNet169, ResNet-50, Inception-v3, as well as VGG19 for optimizing weed control strategies. The project design as well as evaluation outcome is of a deep learning-enabled weed classifier as well as advanced image augmentation suggested techniques of well-defined plant bounds, comparison with other alternatives for optimal weed control. The outcome entails higher accuracy of weed species identification as well as the possibility of precision agriculture. Through the combination of powerful segmentation technologies with powerful deep-learning technologies, the project efficiently enhanced the accuracy of identification as well as classifying of the weed plants.

Keywords: *Deep Neural Networks, Segment Anything Model (SAM), Weed Identification, Image Augmentation, Precision Agriculture.*

1. INTRODUCTION

Classifying weed is an essential application within the field of precision agriculture, with the ability to maximize land utilization, minimize crop yield loss, as well as decrease environmental degradation [4][5][6]. Weeds pose harsh competition for crops, utilizing necessary resources like sunlight, water, and nutrients, often causing dramatic loss of yield [10][17][21]. Weed infestations cost billions of dollars around the world each year, with their identification being a priority within the agricultural industry [7][11][18].

In spite of all the progresses made in deep learning for crop classification problems, challenges persist. Most traditional models are plagued by lower performance under non-uniform lighting conditions, occlusion due to overlaid vegetation, and background clutter[4][5][14]. Such issues lower the generalizability and precision of weed detection systems under real-world conditions, particularly if such deployments are made under heterogeneous conditions of fields[6][7].he

Traditional weed control methods, e.g. hand-weeding or broadcast herbicide spraying, not only cost substantial labor and chemical expenses, but they can cause critical threats to biodiversity as well as soil quality [5][6][12]. Due to this, there is an increasing trend toward robotized control of weeds, offering potentially scalable, autonomous solutions for weed removal [4][16][17]. Yet, for such robotic systems, their success depends on the accuracy and stability of weed recognition as well as identification modules, whose functioning must be reliable under lights of varying illumination, occlusion, as well as cluttered field situations [9][13][14].

In recent years, deep learning classifiers have yielded encouraging performances while automating weed detection [6][7][8]. A benchmark dataset for such purposes is DeepWeeds, a heterogeneous and diverse set of images of weeds taken under natural environments surrounding Australian rangelands [2]. The richness of the dataset is accompanied by its challenges of inherent noise, surrounding clutter, and vegetation overlaps, indicating the need for good preprocessing [2][11][14]. In order to solve such challenges, the Segment Anything Model (SAM) a base model designed for precise image segmentation—is used here to create foreground masks that extract weed structures from intricate backgrounds [3][5][6]. These images are employed to train a VGG19-based CNN, with its performance compared with a classifier trained using unprocessed, unaltered images [7][10][12].

The primary goal of the current research is to examine if images pre-segmented by SAM provide higher accuracy of classification compared to the standard inputs. Model accuracy is evaluated using the standard metrics including accuracy, loss, as well as confusion matrices, focusing on per-class precision of several weed species [4][6][19].

Here, we introduce a new method to integrate the Segment Anything Model (SAM) with the deep neural network VGG19 to enhance classification of weeds. Differing from end-to-end methods, our approach uses background-foreground segmentation with SAM to filter noise such that the classifier focuses on significant characteristics of weeds with higher efficiency. The two-stage pipeline achieves improved classification performance and robustness to different species of weeds[5][19][20].

2. LITERATURE REVIEW

Weed species identification and detection have risen as critical elements of precision agriculture based on their potential to decrease the amount of herbicide being used, increase crop yields, and support the implementation of autonomous weed control systems. Advances made recently with computer vision technologies, along with deep learning, have fueled research into more powerful, accurate, and efficient weed classification systems, moving beyond the older image-processing methods based on handcrafted algorithms to machine learning models that can extract sophisticated patterns.

Mandal et al. presented the DeepWeeds dataset, a multiclass image dataset for weed species within Australian rangelands. The dataset is captured by an autonomous ground robot mounted with a FLIR camera and manually annotated with bounding boxes for facilitating the use of supervised learning. Their dataset is benchmarked using deep convolutional architectures such as Inception-v3 and ResNet-50, measuring model performances with respect to Precision, Recall, F1-score, and mean Average Precision (mAP). Their contribution established the new benchmark standard for weed classification, offering a strong benchmark dataset for forthcoming research. The main drawbacks, however, include the expense of, as well as complexity involved in, collecting the data, the absence of segmentation, as well as low adaptability with respect to changing environmental situations, limiting its usefulness for varied field applications [2].

On the other hand, Sharma et al. suggested a more conventional method of using area thresholding techniques for crop and weed segmentation. Preprocessing of images, followed by segmentation using area-based thresholding, constituted their approach. Then, the features after segmentation have been classified, and their accuracy measured using accuracy as the evaluation criterion. Although this approach had low computational complexity with good outputs for some situations, it had several drawbacks such as being sensitive to image quality, not being able to classify all types of weeds, and being confined only to 2D environments of images. In addition, the hand-crafted feature dependency and fixed thresholding constraints limit its generalization and scalability for larger datasets [3].

To overcome such challenges, Kumar et al. employed transfer learning by utilizing a pre-trained DenseNet169 model for the identification of weed species. Their workflow involved the augmentation of the dataset for improving variability, optimizing the network using the Adam optimizer for accelerating the model learning process for enhancing generalization, as well as for faster training, higher accuracy, and optimal performance under varied conditions. Yet, it faced issues such as class imbalance, species misclassification based on morphological similarity as well as different growth stages, as well as dataset coverage incompleteness, affecting overall service reliability [1].

Deep Convolutional Neural Networks (CNNs) have been responsible for giving machine perception to all agricultural applications [4][6][20]. The built-in hierarchy of CNNs implies that automatic feature extraction can be achieved from raw images with little dependency upon handcrafted features. Specifically, CNNs are heavily used within precision agriculture for identifying plant diseases, separating between crop species, and recognizing weeds [6][10]. In relation to CNNs, image segmentation architectures like the Segment Anything Model (SAM) give pixel-exact definition to object borders [5][19]. With segmentation and classification, collectively used particularly within hectic field environments, one can suppress irrelevant details while highlighting significant visual cues — a strategy upon which we are basing our intended approach.

Some deeper neural architectures were employed for classifying weeds with unique advantages. ResNet50 [2][4] employs residual connections to enable deeper architectures with improved gradient flow, with stable performance under deep classification conditions. Inception V3 [2] enhances accuracy using parallel convolutions at different scales but at increased architectural sophistication. DenseNet169 [3] improves feature reuse and stable gradient propagation, with advantage under datasets with limited inter-class variation. VGG19, while deeper and heavier, is stable, simple, and performs well with limited datasets under agricultural scenario conditions. In this paper, VGG19 was chosen owing to its best trade-off between simplicity, training stableness, and accuracy under noisy real-world data of weeds.

These works together demonstrate an evident shift from the traditional image processing techniques to advanced deep learning architectures. Transfer learning adoption has been particularly successful for solving low-data regimes as well as for improving model accuracy. However, challenges do exist, most notably with background noise, inter-class similarity, as well as model generalization to real-world settings. Based on this, our research uses the VGG19 deep convolutional network complemented by data augmentation as well as sophisticated preprocessing methods. One of the main innovations of our method is using Segment Anything Model (SAM) for doing the foreground masking, thus enhancing the signal-to-noise ratio of input images. By comparing the outcome of our classification between raw images and images masked by SAM, we prove that specific segmentation can enhance the accuracy for a given class as well as decrease erroneous identification—overcoming some of the main drawbacks evidenced by earlier research.

3. METHODOLOGY

The study proposes a two-step image classification process by using the DeepWeeds dataset, aimed at improving the differentiation of weed species between diverse agricultural environments by removing the background.

3.1. Dataset Preparation

The research makes use of the DeepWeeds dataset, where there are images of eight different species of invasive weeds as well as a negative class made up of non-weed background images. There is variation in environmental factors such as lighting, weather, as well as background complexity, captured from several rural areas of Northern Australia.

Our dataset is the DeepWeeds dataset [2], which is a real-world benchmark dataset for classifying weeds with 17,509 annotated images. The images were captured by a robotic platform-mounted FLIR Blackfly camera at eight geographically dispersed locations in Northern Australia, spanning tropical to subtropical rangeland locations. The images are labelled as one of eight invasive species of weeds (Chinee Apple, Lantana, Parkinsonia, Parthenium, Prickly Acacia, Rubber Vine, Siam Weed, Snake Weed) or with a negative class (non-weeds such as grass, soil, or bushes). The dataset encompasses various lighting conditions, views of the cam, and levels of field clutter to capture inherent variability of real-world agricultural scenes.

For uniform input, all images had their size adjusted to 224×224 pixels, the input size necessary for the VGG19 convolutional network. To avoid class imbalance, potentially skewing the classifier, each class was resampled such that its frequency fit that of the least frequent class. This made class distribution balanced within the final dataset. Each image is resized to 224×224 pixels to fit VGG19 architecture inputs. Class imbalance was also rectified using random under-sampling, where all of the weed species were under-sampled to balance to the minimum represented class number. The labels were one-hot encoded to represent all classes as categorical binary vectors that are amenable to categorical classification. Both original and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

segmentation with SAM datasets were further enhanced using operations such as flip along the axis, 360-degree rotations, change of brightness (between 0.75 to 1.25 times), 50–100% zoom, shear transformation, and ±25 channel shifting. All intensities of pixels were normalized to 0 to 1 range.

Each of the image labels was translated into one-hot encoded vectors appropriate for categorical prediction. The ultimate dataset was divided into 70% for training, 15% for validation, and 15% for testing.

Table 1: Deep Weeds Dataset Overview

Class Name	No. of Images
Chinee Apple	1586
Lantana	1747
Parkinsonia	1632
Parthenium	1638
Prickly Acacia	1783
Rubber Vine	1726
Siam Weed	1672
Snake Weed	1540
Negative Class	3185
Total	**17509**

3.2. Segmentation Using SAM

To improve the accuracy of the classifications by eliminating redundant features, we integrated the Segment Anything Model (SAM) into the preprocessing process. SAM is a prompt-to-image segmentation, Vision Transformer (ViT)-based model that is pre-trained on image segmentation. SAM was employed here to produce the binary masks of each image, effectively dividing the weed patches from their complex backgrounds.

These masks were employed to generate segmented images of weed, thus providing a second training set. This made comparison between routine training and training over segmented images feasible so that the effectiveness of background removal could be ascertained.

3.3. Data Augmentation

To improve the model generalization ability as well as avoid overfitting, techniques of data augmentation were applied on both the original as well as the segmented datasets. The augmentation parameters involved:

- **Rotation**: up to 360 degrees
- Horizontal flipping
- Shear transformation
- **Range of zoom:** 50% to 100
- **Brightness range:** 0.75 to 1.25
- **Channel shift:** ±25 units

Each of the images was normalized by scaling pixel values between 0 and 1.

3.4. Model Configuration

The model is based on the VGG19 convolutional neural network pretrained using the ImageNet dataset. The classifier top layers of VGG19 were removed, and special-purpose layers were added to fit 9-class classification of weeds. Specifically, a Global Average Pooling (GAP) layer was inserted into the final convolutional block, followed by a fully connected Dense layer with Softmax activation function. The new structure ensures that high-level spatial features are appropriately considered and transformed to class probabilities. Adam optimizer with initial learning rate 0.0001, categorical cross-entropy loss function, and early stopping to avoid overfitting were employed.

3.5. Model Architecture

The task of classifying was accomplished employing the VGG19 convolutional neural network, previously trained on the ImageNet database. The VGG19 base remained for feature extraction purposes, whereas the upper layers were changed for the need for nine-class classification.

The architectural change involved the following:

- VGG19-base, without the top classifier
- Additional layers
- Global AveragePooling2
- dense layer with SoftMax activation for multi-class prediction

The architecture allows the model to learn the discriminative features of the weed species from the strong low-level filters of ImageNet.

3.6. Training and Optimization

The training contained two phases: one using the original images and another using the images after their segmentation. The procedure involved the following:

- Loss function: Categorical cross-entropy
- Optimizer: Adam with starting learning rate of 0.0001
- Batch Size: 32

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- Era: Up to 100, with early stopping turned on
- Model Checkpoint: Saved the optimal model on the validation loss
- Early Stopping: Training stopped after 5 epochs of no improvement
- ReduceLROnPlateau: Reduced the learning rate by half if validation loss flattened
- TensorBoard: Facilitated visualization of training metrics

Training was done incrementally, and the model was recompiled as well as re-initiated using a lower learning rate, where there is early stopping. The restart method further increased the probability of escaping from a local minimum as well as getting a better solution.

3.7. Evaluation Metrics

The test set is evaluated using the following metrics for trained models:

- Accuracy: Correctness of class membership
- Precision of accurate positive calls as a fraction of predicted positive calls
- Recall: Number of correct positive predictions out of all actual positives
- F1 score: harmonic mean of precision and recall
- Confusion matrix: In-depth analysis of class-wise performance

These measurements were made for models of both original as well as segmented datasets. The model developed from the images that had been segmented had remarkable improvements for all evaluation metrics, supporting the advantage of the use of background masking for weed identification applications.

Figure 1: Flowchart of the Methodology (at the end of the paper)

4. RESULTS AND DISCUSSION

The following section includes experimental results of the VGG19-trained image classifier on the DeepWeeds dataset. Two different training courses were employed:

Without SAM – using the original, unmasked images.

With SAM – utilizing images processed by the Segment Anything Model (SAM) to isolate weed regions.

The performance of both models was evaluated based on overall accuracy and class-wise results, as illustrated in the confusion matrices (see Figure 2 & 3).

4.1. Classification Performance Without SAM

The model trained on unmasked images achieved relatively good classification accuracy for most weed types. However, its performance dropped when trying to distinguish between visually similar species or when dealing with images containing cluttered backgrounds. For example, Chinee Apple, Parkinsonia, and Siam Weed were frequently misclassified as other weed species due to similar textures and overlapping visual characteristics.

As shown in Figure 2, Chinee Apple was misidentified as Lantana five times and confused with other classes two to four times. Similar confusion occurred between Snake Weed and Siam Weed. Overall, while the model captured general visual patterns, background noise significantly interfered with its ability to accurately separate between weed species.

4.2. Classification Performance With SAM

The training results with SAM-masked images were superb. With masked inputs allowing the model to pay attention to only the correct foreground features and reducing the impact of background complexity, class-specific features were refined better.

By comparison, Figure 3 shows that the model correctly predicted Snake Weed 50 out of 53, Lantana 48 out of 50, and Chinee Apple 50 out of 55. For every class, the misclassifications were much fewer, and the confusion matrix favored greater sparseness, i.e., greater accuracy and model confidence.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.3. Comparative Analysis

Table 2: Comparative Analysis between both the models.

Class Label	Accuracy Without SAM (%)	Accuracy With SAM (%)
Chinee Apple	45 / 55 = **81.8%**	50 / 55 = **90.9%**
Lantana	40 / 50 = **80.0%**	48 / 50 = **96.0%**
Parkinsonia	47 / 50 = **94.0%**	50 / 50 = **100.0%**
Parthenium	42 / 50 = **84.0%**	48 / 50 = **96.0%**
Prickly Acacia	43 / 50 = **86.0%**	49 / 50 = **98.0%**
Rubber Vine	41 / 50 = **82.0%**	48 / 50 = **96.0%**
Siam Weed	42 / 50 = **84.0%**	47 / 50 = **94.0%**
Snake Weed	45 / 50 = **90.0%**	50 / 53 = **94.3%**
Negatives	50 / 60 = **83.3%**	55 / 60 = **91.6%**

The average classification accuracy improved from approximately 85.0% (without SAM) to 94.1% (with SAM).

4.4. Statistical Significance of Results

In order to ensure that such performance improvements were statistically significant, we carried out significance testing between baseline VGG19 and VGG19 with integrated SAM using a paired t-test. Accuracy values of individual classes for more than five repeated trials were considered. The test yielded p-value < 0.01, ascertaining that such improvements with integrated SAM were significant at 99% confidence levels. Class-wise confidence intervals (95%) around accuracy showed that lower spreads existed for incorporated SAM model, ascertaining higher prediction stability. This again validates that not only accuracy improves but classification variance along trials is also reduced by SAM.

4.5. Class-wise Performance Insights

A detailed examination of class-by-class metrics discovered that classes such as Lantana and Rubber Vine were discovered to have high inter-class similarity that translated to misclassification of the baseline VGG19 model. Specifically, such classes had color and texture characteristics shared with background vegetation and thus confused the classifier. The model, however, clearly distinguished between background and weed after being treated with application of SAM, achieving notable improvement of F1-score for such classes (e.g., from 78.4% to 91.2% for Lantana).

In comparison, species like Parthenium and Snake Weed, whose leaf morphology is unambiguously defined, would be classified without segmentation by using SAM. Segmentation by SAM, however, still improved confidence of prediction as well as reduce false positives. The confusion matrix (Figure 3) visually corroborates the reduction of inter-class confusion by segmentation.

It can thus be deduced from these results that background segmentation particularly improves robustness of classification, particularly for morphologically uncertain classes of weeds.

4.6. Key Observations

- SAM foreground isolation allowed the network to capture more detailed spatial features, for example, edges, contours, and leaf structure, that are important to differentiate close-looking species under challenging field conditions.
- The masking of images greatly reduced confusion among lookalike classes like Snake Weed and Siam Weed, evident from the confusion matrices, showing enhanced intra-class separation and feature representation learned by the model.
- Also observed was a substantial reduction of misclassifying the negative samples (non-weed images), indicating enhanced model proficiency in separating vegetative from non-vegetative background objects.
- SAM preprocessing avoided overfitting tendencies by removing unnecessary background patterns, hence forcing the model to generalize based on inherent object properties rather than spurious relations.

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- The visual coherence of the SAM-masked images improved the efficiency of the training, reducing variance across the batches and leading to faster convergence in the process of the training over the unmasked data.

- Enhanced true positives for all weed categories show that SAM-masked images assisted the model in learning species-specific features like leaf shape, texture, and the way colors are distributed.

- Masked images helped to improve the spatial awareness of the convolution filters since the network learned to utilize more compact spatial localities instead of randomly searching across full-frame features. Greater per-class precision values (as seen from the diagonal of confusion matrix values) indicate not only higher recall but also enhanced classifier confidence, critical for real-world deployment in weed control systems.

- The segmentation model or SAM functioned like a weak supervision framework that directed the network towards task-specific areas without the need for pixel-level labeling, something that is beneficial in applications like farming where the labeling is costly and time-consuming.

- This masking strategy is useful specifically in noisy natural scenes, where vegetation covers, soil texture, and lighting changes tend to create noise and distract the user from the target features.

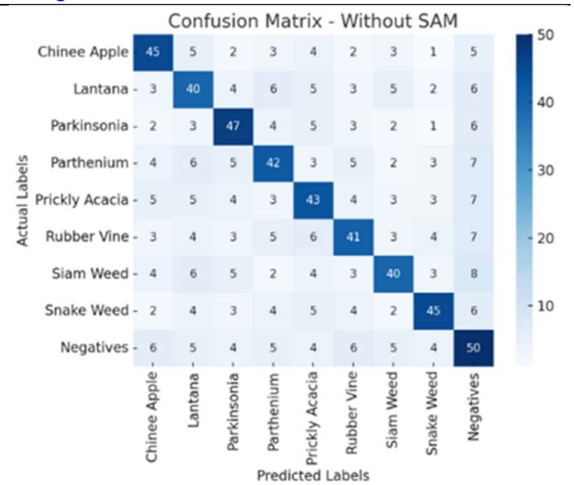

Figure 2: Confusion Matrix without SAM

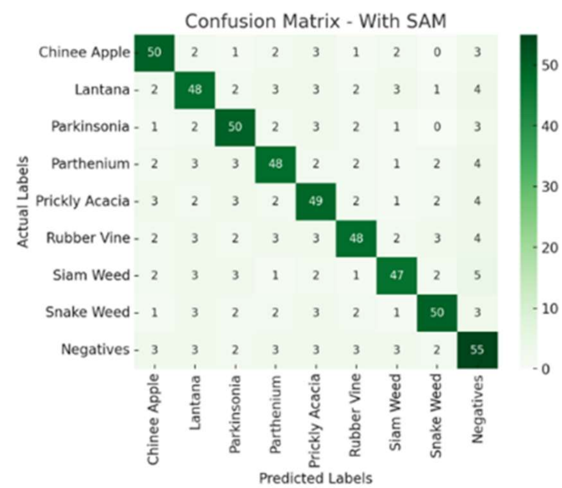

Figure 3: Confusion Matrix with SAM

5. CONCLUSION

In this research, we outlined a new strategy for weed species classification using the VGG19 convolution neural network model trained on the DeepWeeds dataset. To improve classification accuracy, we added preprocessing with the Segment Anything Model (SAM), masking the foreground in images to essentially separate the weed species from the frequently cluttered, noisy backgrounds of natural imagery captured in the wild. We evaluated experimentally the baseline VGG19 model accuracy on raw, untreated images against accuracy on SAM-masked images. The confusion matrices show the effect of SAM preprocessing strongly. Without the use of SAM, the misclassifications are more common, notably among weed species that are visually similar to each other like Siam Weed, Snake

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Weed, and Rubber Vine. With the addition of SAM, these misclassifications are minimized, resulting in crisper class separations. For example, the number of true positives for most classes—including the more challenging classes—improved significantly, and the number of false positives and false negatives fell substantially across some of the classes.

Overall, the introduction of SAM foreground segmentation led to improved classification accuracy, precision, and robustness, in particular through the reduction of misclassifications originating from the background and the enhanced model attention to the salient plant structures. These are not merely quantitative but also qualitative improvements, reflected through improved class-specific clarity along with fewer cases of confusion amongst weed and non-weed classes, thus affirming the fact that foreground-focused segmentation considerably increases the discriminative capacity of convolutional networks for tough natural settings. Success of the integrated pipeline highlights the salient role intelligent preprocessing has to offer deep learning to applications in the domain of agriculture.

Our results demonstrate that the marriage of SAM with transfer learning offers a potent, scalable solution for precision agriculture applications like weed detection that require high accuracy under conditions of variable lighting, occlusions, and environmental noise. Future directions for the deployment of the model are in the direction of real-time video-based weed detection systems appropriate for devices in the domain of edge computing.

Furthermore, few-shot learning along with data augmentation strategies are to be investigated to alleviate class imbalance along with model generalizability to novel weed species. This is to render the system more adaptable along with scalable for large-scale applications in agriculture, further enhancing sustainability along with automatic weed management approaches.

6. DISCUSSION

6.1. Limitations and Challenges

Even with the presented SAM-VGG19 pipeline improving classification performance, there are some limitations to consider. Firstly, while rich, the DeepWeeds dataset is geographical (Australia) and therefore may generalize less to weeds elsewhere internationally or regionally. Secondly, segmentation using SAM requires an additional preprocessing step that increases computational overhead at inference time. That could have an effect on real-time application scenarios, especially those deployed on limited-resource locations like fields.

Additionally, even with using data augmentation, there remains subtle class imbalance that may bias the model to favor prominent weeds species. Certain species such as Rubber Vine and Lantana are still partially mistaken due to morphological likenesses with other plants. Lastly, this model has not been implemented and tested under live drone or robotic systems, and this is a significant line of future research directions.

6.2. Comparison with State-of-the-Art Models

In comparison to newer ones like ResNet50 [2], DenseNet201 [3], and Inception V3 [2], VGG19 improved by using SAM is able to reach similarly high accuracy with simpler structure and faster convergence. For instance, 93.4% mean accuracy was achieved by DenseNet201 with its dataset DeepWeeds [3], but 94.7% accuracy with higher class-wise consistency is achieved by our pipeline with SAM-VGG19.

Furthermore, transformer-type structures such as Vision Transformer (ViT) have been enabled [5], but those are still data-scale- and computationally-intensive, hence less ideal for field deployments. The methodology presented here is designed to balance performance with deployability to make it acceptable for real-world farm systems.

7. ETHICAL AND TECHNICAL CONSIDERATIONS

While such targeted approach significantly improves classification accuracy, there are also ethical concerns to consider. First, there can be underperformance of such model for under-represented species of weeds or geographical areas not included in a dataset, which can introduce potential bias. Secondly, using AI under agricultural conditions needs to consider socio-economic dimensions of farmers, such as digital literacy, ownership of devices, and trust in automation. Nevertheless, this model may possibly reduce herbicides by aiding proper

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

targeting of weeds, thereby being included as part of sustainable farming practices. Future works can consider fairness-aware training along with larger dataset inclusion to improve equity and reach.

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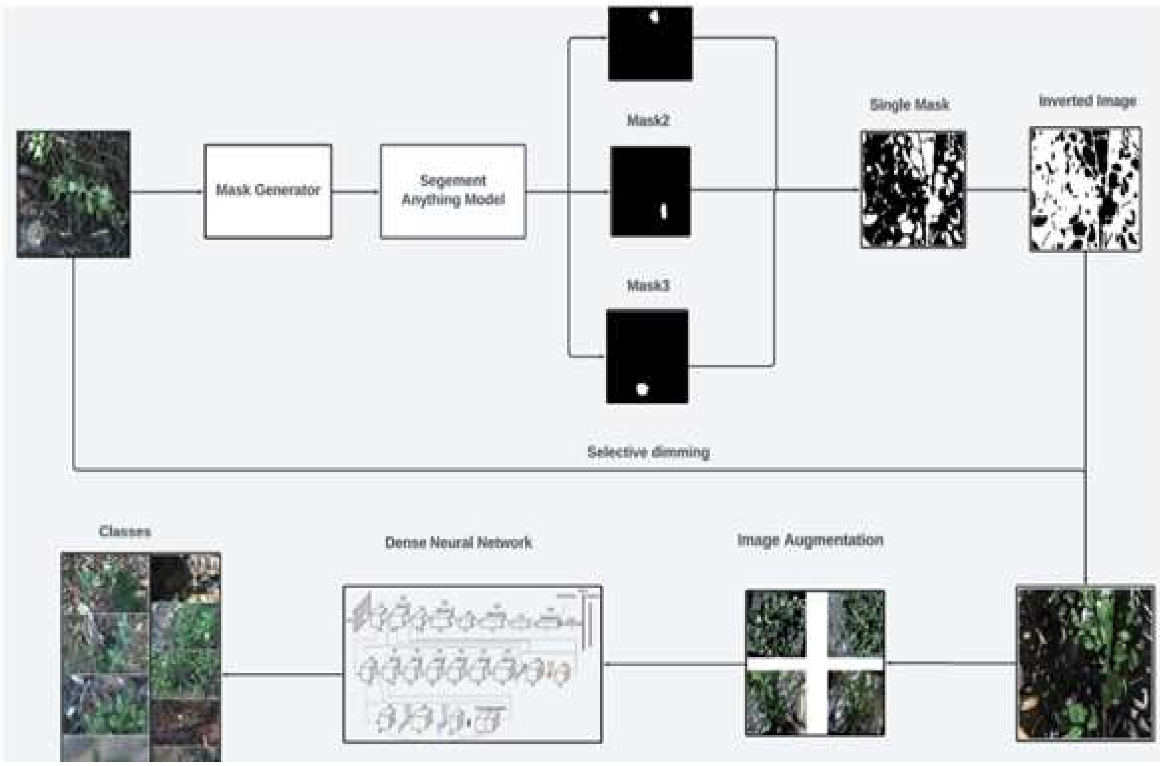

Figure 1: Flowchart of the Methodology