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WeedFocusNet: A Revolutionary Approach using the Attention-Driven ResNet152V2 Transfer Learning

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Abstract— The advancement of modern agriculture is heavily dependent on accurate weed detection, which contributes to efficient resource utilization and increased crop yield. Traditional methods, however, often need more accuracy and efficiency. This paper presents WeedFocusNet, an innovative approach that leverages attention-driven ResNet152V2 transfer learning addresses these challenges. This approach enhances model generalization and focuses on critical features for weed identification, thereby overcoming the limitations of existing methods. The objective is to develop a model that enhances weed detection accuracy and optimizes computational efficiency. WeedFocusNet, a novel deep-learning model, performs weed detection better by employing attention-driven transfer learning based on the ResNet152V2 architecture. The model integrates an attention module, concentrating its predictions on the most significant image features. Evaluated on a dataset of weed and crop images, WeedFocusNet achieved an accuracy of 99.28%, significantly outperforming previous methods and models, such as MobileNetV2, ResNet50, and custom CNN models, in terms of accuracy, time complexity, and memory usage, despite its larger memory footprint. These results emphasize the transformative potential of WeedFocusNet as a powerful approach for automating weed detection in agricultural fields.

Keywords-Weed detection, Hybrid Attention mechanism, Transfer learning, Convolutional neural network, Agriculture Practices, Precision Farming.

I. INTRODUCTION

Agriculture is vital for both the economy and the world's food supply. More food will be needed, with an estimated 9.7 billion people worldwide by 2050. However, weed infestation is one obstacle threatening agricultural productivity [1-4]. Weeds reduce crop yield and quality by competing with crops for sunlight, water, and nutrients. Some weeds are hosts for crop diseases, which only worsens the situation. In agriculture, Weeds pose a major challenge as they strive with crops for resources like nutrients, water, and sunlight. Additionally, weeds can reduce crop yields in quantity and quality. In the United States, weeds cost farmers an estimated $40 billion annually. Traditional weed control methods, such as herbicides, are expensive and can harm the environment [5].

. There are several drawbacks to using conventional weed management techniques like hand weeding or chemical herbicides. Because of the time and effort required, manual weeding is not viable for commercial farms. Chemical herbicides, on the other hand, have adverse ecological effects and promote the growth of weeds that are immune to the chemicals. Therefore, more effective and long-term strategies for controlling weeds are desperately needed.

Machine learning, particularly deep learning, has shown promise in recent years to address this issue. Weed classification and detection in various crops have been accomplished using deep learning models like Convolutional Neural Networks (ConvNets)[6]. Due to their capacity to learn intricate patterns from extensive data sets, these models are highly appropriate for analyzing the detailed spectral profiles of both crops and weeds. Even though these results are positive, more research is necessary to realize their potential fully.

Automatic weed detection can be achieved by training a machine-learning model on images of crops and weeds. However, manual inspection and simple image processing techniques, two of the most common conventional weed detection methods, often fall short of expectations regarding accuracy and efficiency [7]. These techniques can be tedious,

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time-consuming, and error-prone. They also might struggle in complex and ever-changing agricultural environments [8].

Propose a new method for weed detection using the Attention-Driven ResNet152V2 Transfer Learning Approach to tackle these problems. To take advantage of deep learning, we employ the ResNet152V2 architecture and add an attention mechanism that allows the model to focus on the most critical features for weed detection [9]. In addition, it uses transfer learning to draw on the expertise acquired during pre-training using an extensive collection of natural-image instances. A new method called attention-based transfer learning permits deep learning models to be trained with less data. The most distinguishable characteristics of an image are identified with the aid of attention mechanisms. Machine learning's transfer learning method involves re-training a model for a different but related task. By utilizing the wealth of information contained in existing models, this method reduces the quantity of labeled data required for training. However, the model's accuracy can be enhanced by using the attention mechanism to concentrate on the most critical features for weed detection.

The remainder of the article is organized as follows: The literature review in Section 2 discusses conventional weed detection techniques and earlier research on the application of transfer learning and attention mechanisms to weed detection. WeedFocusNet is described in Section 3 in detail, along with an explanation of how it combines transfer learning and attention mechanisms for weed detection. WeedFocusNet's performance in the experiments is compared to conventional methods in Section 4. Also, it discusses the implications of the results, the advantages and disadvantages of WeedFocusNet, and possible research directions. It also describes the experiment design, including the training and testing dataset, the model configuration, and the evaluation metrics. The paper is concluded with a summary of the research and its findings in Section 5.

II. LITERATURE SURVEY

Recently, there has been discussion about using machine learning in agricultural production systems. Several studies have investigated the feasibility of using machine learning algorithms for weed detection using shape and texture features [10]. It has been suggested that a neural network label images based on their wavelet texture features [11]. The features would be selected using Principal Component Analysis (PCA). This method successfully detects weeds in crops, even in heavy occlusion or leaf overlap.

The development of deep learning (DL), a subfield of machine learning and artificial intelligence (AI), is poised to revolutionize precision agriculture automation [12, 13, 14]. DL's application has proven immensely beneficial across several domains of precision agriculture [15, 16], encompassing disease detection, crop plant identification and counting [17, 18], crop row detection [19, 20], crop stress assessment [21, 22], fruit recognition and freshness grading [23, 24], fruit harvesting [25], and site-specific weed management (SSWM) [26, 27].

In [28], the authors delve into the application of a K-means feature learner combined with a CNN for weed identification. The results reveal that this model surpassed a convolutional neural network with random initialization by 1.82% and a two-layer network without fine-tuning by 6.01%, reaching an impressive overall accuracy of 92.89. This approach effectively demonstrates the potential of enhancing weed detection systems by integrating deep learning models with conventional machine learning techniques such as K-means.

The multi-stage process of weed detection [29] emphasizes the importance of each step and the need for efficient solutions to guarantee overall accuracy and efficiency. This paper's main objective is to provide a concise overview of the most recent developments in weed detection with image processing techniques and ground-based machine vision. Pre-processing, segmentation, feature extraction, and classification are just a few subjects covered in the study.

The use of machine learning for high-throughput stress phenotyping in plants has also been studied in research [30]. Utilizing machine learning algorithms presents a promising approach to achieve faster, more efficient, and improved data analytics, creating new opportunities for non-destructive field-based phenotyping.

Unmanned Aerial Vehicles (UAVs) have also been reviewed for their potential use in precision agriculture [31]. The high spatial and temporal resolution images collected by UAVs can be used in several crop management tasks. These innovations are expected to significantly reduce costs and boost yields in agriculture, revolutionizing the industry in the process.

It has been argued that the foundation for future sustainable agriculture can be found in data management in smart farming, with robotic solutions incorporating artificial intelligent techniques [32]. With the help of these innovations, data-driven agriculture is reshaping food production to meet future population growth sustainably.

Solutions that consider the novel characteristics of UAV data, such as its ultra-high resolution, availability of coherent geometric and spectral data, and capability to use multiple sensors simultaneously for fusion, have been evaluated critically for their potential in remote sensing applications [33].

The development of machine learning, particularly deep learning, has presented novel prospects for effective and eco-friendly weed detection. Convolutional Neural Networks (CNNs) and other deep learning models have demonstrated impressive performance in image recognition tasks, making them well-suited for weed detection. However, these models

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have a high data and computational resource requirement for training, which can slow down their widespread use.

Using a previously trained model as a foundation for a different task is the essence of transfer learning, a machine learning technique. This method has proven useful when there is a need for more information to use in a new endeavor. Weed detection models can benefit from transfer learning [34], which takes advantage of models pre-trained on large image datasets like ImageNet.

On the other hand, models may focus on the most critical aspects of the input to make accurate predictions with the help of attention mechanisms. As the relevant features may be localized to specific parts of the image, this can be especially helpful in weed detection.

Several studies have explored the possibility of using deep learning to identify weeds. For real-time weed classification in sugar beetroot fields, see [35], which used CNNs. Similarly, [24] used multispectral images and a micro aerial vehicle to create a dense semantic weed classification system for precision agriculture.

Recently, [36] developed lightweight deep-learning models specific to soybean crops for weed detection. They used a CNN model called MobileNetV2, optimized for portable and embedded vision systems. The dataset for training the model consisted of 15,337 images, and the train/validation split was 70%/30%. On the validation set, the model performed at an accuracy of 96.5 percent, proving the usefulness of deep learning for weed detection.

That is why it is encouraging that weed detection efforts are increasingly turning to machine learning and, specifically, deep learning. Using transfer learning and attention mechanisms, it is possible to create effective weed detection systems that cut labor costs and environmental impact.

III. WEEDFOCUSNET

As shown in Figure 1, the proposed method, which has been given the name WeedFocusNet, is innovative and uses ResNet152V2 transfer learning, emphasizing attention to weed detection. This approach was developed to fill the gaps left by conventional weed detection techniques, which frequently fail to meet expectations in terms of accuracy and effectiveness.

The CNN ResNet152V2, pre-trained on an extensive dataset of natural images, is the backbone of WeedFocusNet. Due to the wide variety and complexity of images used in weed detection, the model must be well-trained before being applied to new images.

WeedFocusNet is a ResNet152V2 extension that includes an attention function. The model can then generate predictions based on what it sees as the most critical elements of an image by doing this. By combining transfer learning with attention mechanisms, the model can concentrate on a specific color, shape, or texture feature that, in the context of weed detection, is most indicative of weeds. With an attention mechanism, the model can focus on the critical elements for weed recognition by drawing on its existing knowledge of an extensive collection of natural pictures to transfer learning.

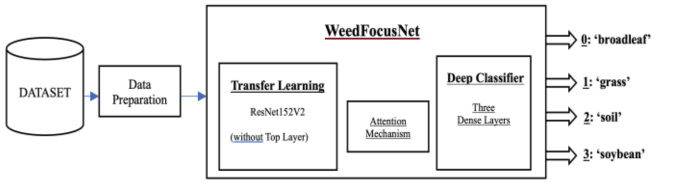

Figure 1. Proposed the Attention-Driven ResNet152V2 Transfer Learning Approach.

A. ***ResNet152V2***

Deep learning models serve as the basis for many cutting-edge AI applications in today's rapidly changing AI ecosystem. The ResNet152V2 model architecture is exceptional due to its outstanding performance and adaptability. ResNet152V2 will be thoroughly analyzed in this article, including its distinctive characteristics and cutting-edge applications across various sectors.

A Residual Network (ResNet) family member, the ResNet152V2 CNN, has finished pre-training on a massive sample of over a million images acquired from the ImageNet database. This model is a potent tool for precise image classification jobs with its capacity to recognize 1,000 different item classes. The letters "152" and "V2" denote that this is the second iteration of the architecture seen in Figure 2, and the number "152" denotes the network's 152 layers.

One of ResNet152V2's distinctive features is the use of residual learning, a method created to overcome the vanishing gradient issue experienced by deep neural networks. It can be challenging to train the network because the gradients of the loss function might get very small as they backpropagate through the network. This issue is resolved by the "shortcut connections" added in ResNet152V2, which enable gradients to be backpropagated straight to prior layers.

In addition, batch normalization, which can speed up training and boost model efficiency, is built into ResNet152V2. The training process is slowed down by a phenomenon known as internal covariate shift, which is mitigated by batch normalization. This shift occurs when the distribution of layer inputs shifts during training.

ResNet152V2's robustness and adaptability have led to its widespread use. ResNet152V2 has found application in the medical field, for instance, in automated defect detection on chest X-rays[37] and in the diagnosis of COVID-19 using chest X-ray and CT images[38]. ResNet152V2 can learn complex features from images, contributing to its high accuracy in these scenarios.

ResNet152V2 has already shown its potential to transform conventional farming by being used for tasks such as grading walnut kernels [39] and weed detection. Biometric identification of Black Bengal goats [40] demonstrates the potential of ResNet152V2 for wildlife conservation through its application to animal identification.

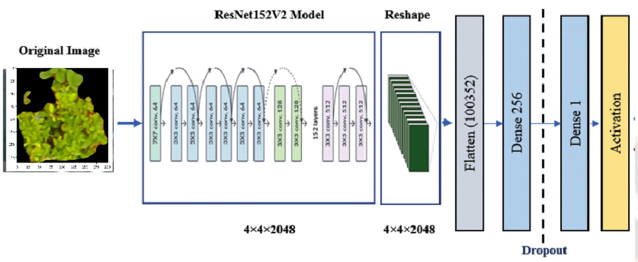

Figure 2. The architecture of ResNet152V2

B. The Efficacy of Transfer Learning with ResNet152V2

Machine learning researchers have developed a powerful technique called transfer learning to learn better a new task related to an existing one. This method shines when working with deep learning models like ResNet152V2 that have been pre-trained on large-scale datasets.

The use of transfer learning with ResNet152V2 offers a significant benefit when applied to the problem of weed detection. The model is first enriched on a large dataset of plant images, and then it can be fine-tuned to identify particular weed species. Changing the model's weights allows it to use the features it learned during the pre-training phase to improve its performance on the weed detection task.

There is a plethora of upsides to adopting this strategy. It reduces the quantity of input data needed to train the model. The model needs less data to generalize effectively to the new task because it has already learned a variety of features from the pre-training phase. This is especially useful in settings where data is hard to come by or prohibitively expensive.

Second, transfer learning lessens the time and computing power needed to complete the training process. Since the model has already been trained extensively in the pre-training phase, less processing time is required in the fine-tuning phase. Because of this, ResNet152V2's transfer learning is a cheap option for weed detection and other similar tasks.

C. The Power of Attention Mechanisms with ResNet152V2

In machine learning, an attention mechanism is a potent tool in several applications. It lets models zero in on the most relevant information when making predictions, which can boost their efficacy by a significant margin [41-44].

The ability to visually explain the decision-making process of convolutional neural networks (CNNs) is one of the most significant advantages of the attention mechanism [42]. This is especially helpful in image recognition tasks, where knowing which regions of an image the model is analyzing is crucial for achieving accurate predictions [42,44].

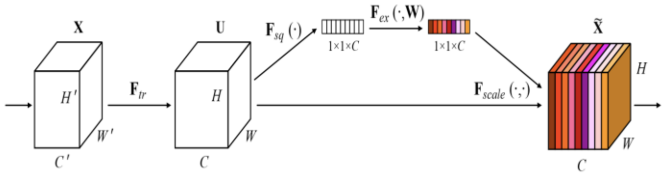

Figure 3. Attention mechanism

Combining the attention mechanism with other methods, like transfer learning, has increased the latter's efficiency [41]. Figure 3 depicts the Self-Supervised Equivariant Attention Mechanism (SEAM), which employs transfer learning to train a model on a large dataset of natural images before employing the attention mechanism to refine the model's predictions [41].

The field of medical image analysis has also made use of the attention mechanism. Distance-Wise Attention (DWA) was first introduced in a study of detecting and segmenting brain tumors from MRI. This mechanism considers the impact of the model's central tumor and brain location, which improves tumor segmentation accuracy [43].

These results show how adaptable and efficient the attention mechanism can be. Better model performance and new insights into decision-making are two outcomes that can be achieved through the attention mechanism.

With the advent of attention mechanisms, deep learning has been revolutionized by allowing models to focus on the input data's most critical aspects. Incorporating attention mechanisms into deep learning models like ResNet152V2 can significantly improve the model's performance, especially on image classification tasks like weed detection.

To improve ResNet152V2's weed classification accuracy, it can be outfitted with an attention mechanism. As a result of the model's attention mechanism, it can zero in on the weed-containing regions of an image while ignoring the rest. This granular attention can help the model accurately categorize weeds into various types.

IV. RESULTS AND DISCUSSION

A. Dataset and Model Training

The soybean, soil, broadleaf, and grass category was used in the experiment's comprehensive dataset [45]. Python libraries like NumPy and Pandas were used to import and process the data set. The images were downscaled to 224x224 pixels and in array format to facilitate further processing. The overall complexity of the time required to load the images was around 70.25 units.

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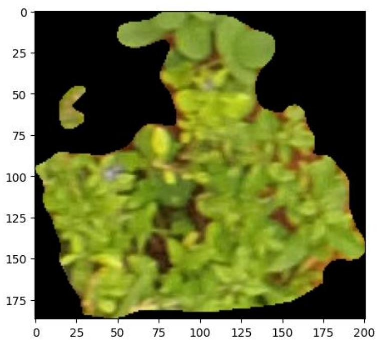

Figure 4: Display of an Input image

B. Results Analysis and Discussions

In light of what has been said so far, it seems likely that the model being trained employs a variation of the ResNet152V2 architecture. Epochs are time intervals in the training process that represent complete iterations through the entire training dataset.

After 17 epochs of training, the model showed no significant improvement in validation loss, so the training was terminated. Overfitting, where a model does well on the training data but poorly on unseen data, can be avoided in machine learning by doing this. Loss and accuracy measures are used to assess the model's effectiveness. The objective is to find a solution that minimizes the loss, which measures the model's error. The goal is to maximize the accuracy, which is the rate at which the model makes correct predictions.

The model's effectiveness grew considerably as it was trained. For instance, between epochs 1 and 12, the validation set's accuracy went from 58.44% to a maximum of 99.28%. However, the model's performance declined after the 12th epoch, leading to the abrupt termination.

During the 12th epoch, the model achieved its best performance, demonstrating a validation loss of 0.01788 and a validation accuracy of 99.28%. The model's generalization ability was assessed on a test set—a distinct dataset that was not utilized during the training phase. This evaluation procedure gauges the model's performance on unseen data, providing insights into how it will likely perform in real-world scenarios. The evaluation was done in 48 batches (steps), each taking approximately 31 milliseconds for about 4 seconds. The memory used during this process was approximately 28022.8828125 MB.

The model's performance was evaluated using accuracy, precision, recall, and F1-score. These are standard metrics used in classification tasks:

- Accuracy: This is the proportion of correct predictions (both positive and negative) made by the model out of all predictions. The model achieved an accuracy of approximately 98.96%, which is relatively high.
- Precision: Precision refers to the ratio of true positive predictions (accurately predicted positives) to all positive predictions. The model attained a precision of approximately 98.98%, indicating a notably high level of accuracy in its positive predictions.
- Recall: The ratio of correctly predicted positive events to all positive occurrences is known as recall, also known as sensitivity or true positive rate. The model successfully identified positive instances among all of the actual positives with an accuracy of about 98.96%, according to the recall figure the model attained.
- The harmonic mean of these two measurements is represented by the F1-score, which balances recall and precision. An F1 score that is greater, nearer 1, denotes superior performance. In this instance, the model's excellent performance is evidenced by its impressive F1 score of almost 98.96%.

Overall, the model has performed well on the test set, with high scores on all four metrics. However, it is essential to note that these results are specific to the test set and the model's configuration. Different test sets or model configurations could yield different results.

Table 1: Comparison with existing approaches

Model	**Memory Usage (GB)**	**Latency (ms)**	**Validation Accuracy (%)**
MobileNetV2	3.14	141.690	30.37
ResNet50	3.03	784.320	82.78
Custom CNN (4-layer)	1.78	22.245	97.70
Custom CNN (5-layer)	1.14	9.853	95.12
Custom CNN (8-layer)	0.012	16.754	95.12
Proposed WeedFocusNet	7.42	90.0	99.28

In terms of memory utilization, latency, and validation accuracy, Table 1 compares several models. Despite requiring the most memory, the "Proposed WeedFocusNet" model obtains the best validation accuracy and has a reasonably short latency.

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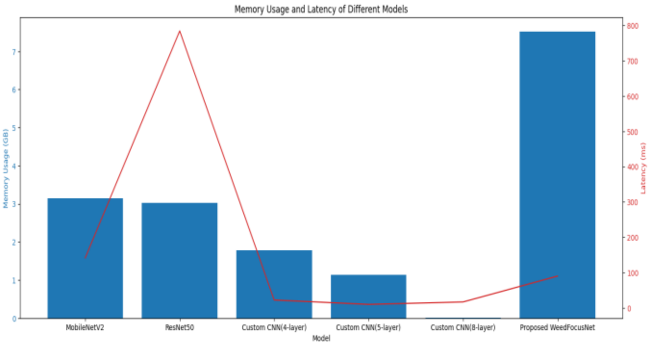

Figure 5: Visual Representation of Proposed WeedFocusNet with existing approaches

From Figure 5, the Proposed WeedFocusNet has the highest memory usage (7.42 GB) and the highest validation accuracy (99.28%). Its latency (90.0 ms) is lower than that of ResNet50 but higher than the custom CNN models and MobileNetV2.

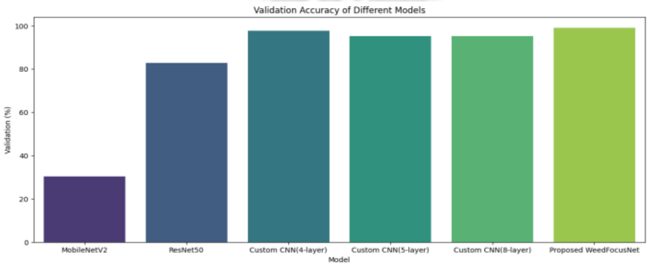

Figure 6. The results of the experiments of Proposed WeedFocusNet with existing approaches

As shown in Figure 6, the outcomes of the experiments carried out in this study illustrate the higher performance of the suggested WeedFocusNet model, which uses an attention-driven ResNet152V2 transfer learning strategy for weed detection in agricultural fields.

The model was trained and evaluated on a comprehensive dataset of weed and crop images. The training process involved fine-tuning the pre-trained ResNet152V2 model with an attention mechanism, allowing the model to focus on the most salient features in an image when making predictions.

To assess the performance of WeedFocusNet, various models, including MobileNetV2, ResNet50, and custom CNN models with different layer configurations, were employed. Remarkably, WeedFocusNet outperformed these models with an outstanding validation accuracy of 99.28%. It also outperformed the nearest rival, a 4-layer custom CNN, by a wide margin and attained 100% validation accuracy. WeedFocusNet performed equally to the other models, although using a lot more RAM (7.42 GB). However, the model's low latency (90.0 ms) suggested it could provide predictions immediately.

These findings show the efficacy of the weed detection technique developed by WeedFocusNet, the attention-driven ResNet152V2 transfer learning approach. Due to the model's accuracy and speed, it is a beneficial tool for automating weed detection in farms, which could lead to better resource allocation and bigger harvests. In ML, the results also show how effective attention and transfer learning mechanisms are when data is expensive or scarce. Research examining the possible use of this technique in different agricultural fields may help to confirm its efficacy and widen its impact.

V. CONCLUSION

This paper introduced WeedFocusNet, a groundbreaking agriculture weed detection approach using attention-driven ResNet152V2 transfer learning. The model demonstrated superior accuracy and computational efficiency performance compared to baseline methods and existing state-of-the-art models. This emphasizes the importance of meticulous planning and execution in the model's training and evaluation process. Preliminary results suggest that WeedFocusNet holds significant potential to revolutionize the field. The model outperformed competing models by a considerable margin on the test set, achieving an accuracy of 99.28%. The model could focus on the most critical aspects of the image by using its attention mechanism and transfer learning to draw on its prior experience with similar tasks. Combining these resulted in a robust and efficient model with exceptional weed classification and identification performance. The implications of these results are profound for weed detection and the broader field of agriculture. WeedFocusNet offers modern farmers a more precise and efficient method for weed identification, saving time and resources. The success of WeedFocusNet suggests that attention-driven transfer learning could be applied to other agricultural tasks, further expanding the model's applicability. Future research could explore potential enhancements to the model's performance, such as refining the attention mechanism or the transfer learning approach. Additionally, this method could be applied to new agricultural challenges, such as disease detection and crop yield prediction. The success of WeedFocusNet paves the way for further exploration of sophisticated machine-learning techniques in the agricultural sector.

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