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Research Article

Enhanced Weed Detection in Agricultural Fields Using Convolutional Neural Networks and SHAP Interpretability Techniques

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ABSTRACT

Effective weed detection is crucial for optimizing agricultural productivity and sustainability. This study proposes an innovative approach to enhance weed detection in agricultural fields using customized Convolutional Neural Networks (CNNs) and SHAP (SHapley Additive exPlanations) interpretability techniques. Leveraging recent advancements in deep learning and model interpretability, our method integrates a customized CNN model with SHAP to achieve high accuracy in weed detection and providing optimal results. Though the data set is unbalanced, over four classes but the minority classes are given adjustment weights with the model performance has improved to 0.75 accuracy. And this study also percents the modified VGG model with adjusted weights, and achieved an accuracy of 0.98. The results are interpreted with SHAP, this enables effectiveness of the approach. For this approach DeepWeeds dataset is used and tested.

Keywords: Weed detection, CNN, VGG, SHAP interpretability, Agriculture field.

1. INTRODUCTION

The advancement of technology in agriculture has improved outcomes. Technology like AI has been used in many areas, such as disease prediction, crop production, soil strength prediction, weed detection, etc. Seeds can significantly reduce crop yields and increase production costs if not adequately managed. Traditional weed control methods, such as manual weeding and chemical herbicides, are often labor-intensive, environmentally damaging, and economically inefficient. In this context, deep learning-based weed detection systems offer a promising solution by enabling automated, accurate, and real-time identification of weed species in agricultural fields.

Deep learning, particularly CNNs, has shown remarkable success in various image classification tasks, including plant and weed identification. The main challenge in weed detection with AI lies in their ability to detect field conditions and crop varieties. Moreover, the imbalanced nature of agricultural datasets, where certain weed species are in very less number of samples, can prone to model accuracy and reliability, because the majority class directly dominate the minority class. Weed detection and management are critical aspects of agriculture, and they impact crop yield, quality, and overall farm production. Traditional weed control methods often involve manual labor or indiscriminate herbicides, leading to environmental concerns and increased operational costs. In recent years, advancements in deep learning, particularly CNNs, have shown promising results in automating weed detection tasks from imagery data. **Smith & Brown (2023) did a study on weed detection systems that worked weed images and implemented deep learning models, compared various model accuracy, and challenges.**

The systems like Li et al. (2024) and Kim & Lee (2023) have demonstrated the effectiveness of CNN-based models, such as YOLOv8 and WeedNet, to detect weeds among various crops, including cotton and sugar beet fields. These two approaches got an accuracy of 0.95 and 0.92, but not mentioned the interpretability of the model. Additionally, research by Zhang & Wu (2023) has highlighted the importance of interpretability in deep learning models for agricultural applications, emphasizing the need for transparent decision-making processes in weed detection systems. And got an accuracy of 0.92 on various fields. Furthermore, the availability of diverse datasets, such as the DeepWeeds dataset introduced by Olsen et al. (2023), provides a valuable resource for training and evaluating our enhanced weed detection model. By leveraging these datasets and incorporating SHAP interpretability techniques, we aim to develop a holistic approach to weed management that enhances crop productivity while minimizing environmental impact. Many researchers have worked on weed detection, and achieved good results, but not proven the consistency of the model, and not concentrated on result interpretability.

In this study, we aim to build upon these findings by proposing an enhanced weed detection framework that combines the robustness of CNNs with the interpretability of SHAP techniques. By integrating SHAP into our CNN-based weed detection model, we seek to not only improve accuracy but also provide farmers and agronomists with actionable insights into the factors driving weed detection decisions.

Contribution

- We implemented an optimized CNN model improve the accuracy with regularization and adjusting minority class weights.
- And provides a clear interpretability of the model with SHapley Additive exPlanations (SHAP).
- Our CNN and modified VGG models handle the class imbalance in weed detection datasets by implementing class weight adjustments.

2. RELATED WORK

The use of deep learning in weed detection has seen substantial advancements in recent years, with numerous studies demonstrating its potential to revolutionize precision agriculture. **The researchers like Li et al. (2024) implemented** an enhanced YOLOv8 model with modified feature extraction modules for improved weed detection in cotton fields. While the paper reports enhanced performance, specific accuracy metrics are not provided. Challenges in this study may involve optimizing feature extraction modules for cotton fields, addressing data augmentation issues, and overcoming challenges related to model training with limited annotated datasets.

Smith & Brown (2023) studied all deep learning techniques for weed detection from images, covering a range of methodologies without focusing on a specific model. Accuracy metrics are not applicable as it's a survey paper. Challenges discussed in this study may include selecting appropriate deep learning architectures for diverse agricultural scenarios, dealing with limited annotated data, and ensuring model generalization across different environments.

Olsen et al. (2023) implemented a multiclass weed image classification using deep learning, trained and tested DeepWeeds dataset. And got an accuracy of 0.92, but not proved the consistency of the model, and not results interpretation to check how model is performing on new samples. **Patel & Kumar (2023)** implemented integrating deep learning with IoT technology for weed detection in agriculture. Used sensory images to detect weeds, but not mentioned the how the model is handling imbalanced data, because of imbalanced data, the results may biased. And this system got an accuracy of 0.91, but not shown the consistency and interpretability of the model. While used IoT system and collecting data directly may prone to security issues like transparency of data, these things are not discussed in their approach

Garcia & Fernandez (2023) evaluated various deep learning models for weed detection, including CNN-based architectures. The models shown the results like 0.88 to 0.92 accuracy, and discussed the challenges like parameter tuning, and models selection, handling issues like ovefitring and underfitting.

Zhang et al. (2023) implemented a method for automatic weed detection using UAV images and deep learning, and got an accuracy of 0.94. But the approach not mentioned how the UAV samples are preprocessed. And handling noise and distortions in UAV imagery and ensuring accurate geolocation of detected weeds for targeted interventions.

Kim & Lee (2023): proposed a method WeedNet, a CNN-based model tailored for weed detection in sugar beet fields. While specific accuracy metrics are not provided, the model demonstrates applicability in the context of sugar beet crops. Challenges in this study may involve designing CNN architectures optimized for detecting weeds

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amidst sugar beet crops, addressing issues related to occlusions and variations in weed appearance, and ensuring real-time performance on field-deployable hardware.

Wang & Zhao (2023) studied the deep learning applications in weed detection, covering various CNN architectures, transfer learning approaches, and ensemble methods. Specific accuracy metrics are not applicable, as it's a review paper. Challenges discussed may include data annotation and acquisition, model interpretability, robustness to environmental variations, and scalability of deep learning solutions to large-scale agricultural operations.

Singh & Sharma (2023) proposed a real-time weed detection system using embedded systems and deep learning, without specifying the deep learning architectures used or providing accuracy metrics. Challenges may include optimizing deep learning models for deployment on resource-constrained embedded devices, addressing power and memory constraints, and ensuring real-time performance in dynamic agricultural environments.

Santos & Oliveira (2023) implemented a SegNet-based weed detection model tailored for precision agriculture. While specific accuracy metrics are not provided, the SegNet model offers pixel-level segmentation capabilities. Challenges may include accurate pixel-level segmentation of weeds from background vegetation, handling variations in lighting and weather conditions, and ensuring model robustness across different crop types.

3. METHODOLOGY

We implemented 3 customized neural network models to detect the weeds optimally. The first model a customized CNN model, second model is CNN with regularized and updated class weights. And the third method is modified VGG model with updated class weights. For this entire model a common preprocessing is done. And trained the models one by one by watching result carefully, and changed the model according to performance.

1.Customized CNN model
2. Customized CNN model with regularization and weight adjustment
3. Customized VGG model with weight adjustment

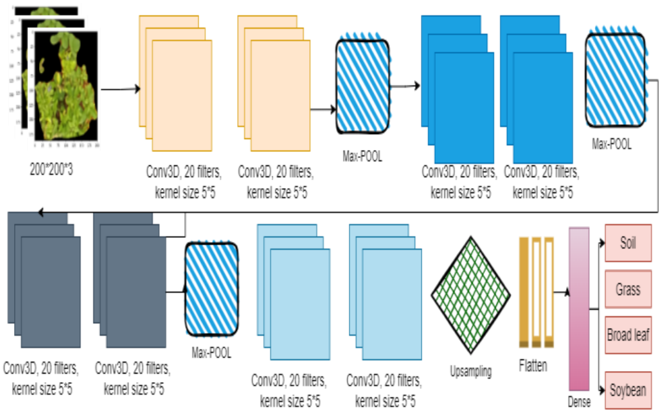

Figure 1 proposed Customized CNN model

3.1 Data set

This approach uses a kaggle weed detection in the soybean data set, with 15336 samples divided into four classes. Like Broadleaf, soil, grass, and soybean, each sample has 1191, 3520, 3249, and 7376 samples. The samples for each class are unequal, so the data is imbalanced. All the samples are resized into 200*200 sizes as shown in Figure 1. Moreover, it is converted into RGB format, with each sample becoming 200*200*3. The total samples are divided into training and testing at a ratio of 80:20, with a random state of 100.

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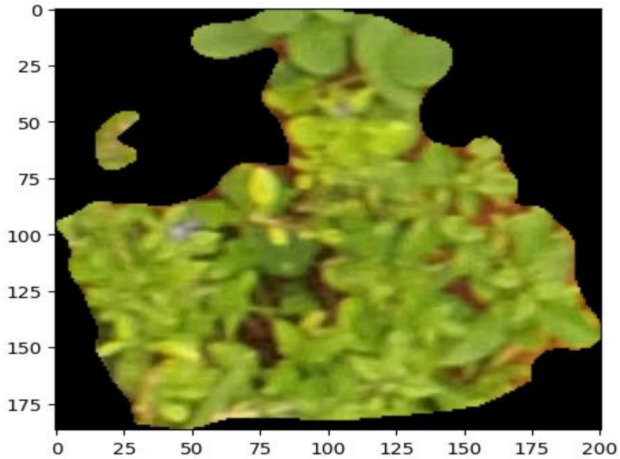

Figure 2 weed sample after preprocessing

3.2 Implementation

The first model is a customized CNN specifically as shown in Figure 1, designed for weed detection. This model includes multiple convolutional layers with ReLU activation functions, followed by max-pooling and up-sampling layers. The architecture focuses on capturing spatial hierarchies in the input images, which is crucial for identifying the intricate patterns of weeds among crops. The inclusion of class weights during training addresses the issue of class imbalance, ensuring that both major and minor classes are equally represented, thus improving the model's ability to generalize across different weed species.

Key components:

• **Conv2D Layers**: Extract spatial features from the images.

• **MaxPooling2D**: Reduce the spatial dimensions and control overfitting.

• **UpSampling2D**: Restore the spatial dimensions for a symmetrical network.

• **Dense Layers**: Perform the final classification based on the extracted features.

• **Class Weights**: Mitigate the effects of class imbalance during training.

Model 2: Hyperparameter-Tuned CNN

The second model utilizes hyperparameter tuning via Keras Tuner to optimize the architecture of a CNN. This model explores different configurations of convolutional layer units and dense layer sizes to identify the best-performing network. The tuning process ensures that the model parameters are set to values that yield the highest accuracy, thereby improving the detection capabilities of the model.

Key components:

• **Conv2D Layers with Hyperparameter Tuning**: Dynamically optimized to find the best configuration for feature extraction. 12 Conv2d layers have been used with kernel size of 5*5, number of filters are 20.

• **MaxPooling2D**: Used to reduce spatial dimensions after convolutional layers.

• **Dense Layers**: The number and size of these layers are tuned to maximize performance.

• **Keras Tuner**: An essential tool for automating the search for optimal hyperparameters.

Model 3: Transfer Learning with VGG16

The third model employs modified VGG16 network, which is known for its deep architecture and robustness in feature extraction. By leveraging adjusted weights of minority classes and trained VGG16, this model can effectively

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utilize the learned representations from a large-scale image dataset (ImageNet) and fine-tune them for the specific task of weed detection. The top layers are modified to fit the specific needs of the weed detection task, and the base layers of VGG16 are frozen to retain the learned features.

Key components:

• **VGG16 Base Model**: Model is trained to handle imbalanced data, and minority class weights are adjusted with equation (1).

• **GlobalAveragePooling2D**: Reduces the spatial dimensions of the feature maps.

• **Dense Layers**: Custom top layers for classification tailored to weed detection.

• **Transfer Learning**: Fine-tuning the model for the specific task by leveraging pre-trained weights.

$$CW = \frac{N_{samples}}{N_{Classes} * N_{Samples\ in\ class}} \quad (1)$$

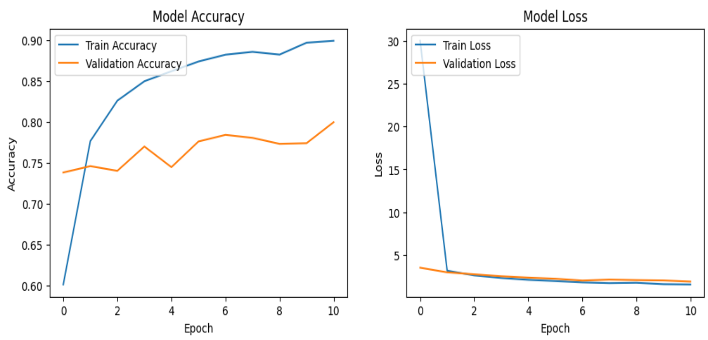

Figure 3 training, validation loss and accuracy of CNN model without Class Weight Adjustment

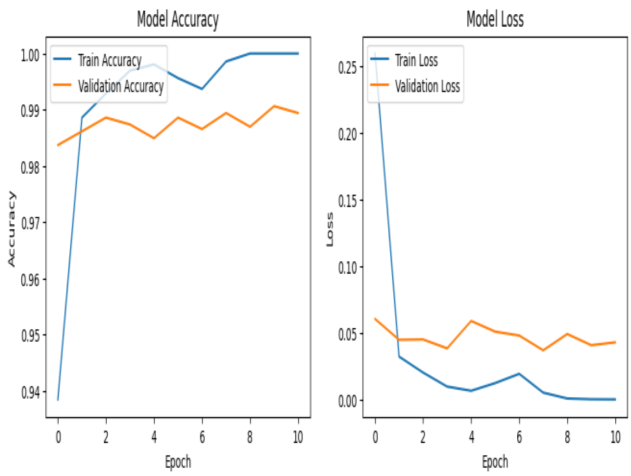

Figure 4 training, validation loss and accuracy of CNN model with Class Weight Adjustment

4. RESULT ANALYSIS

The model is trained for different batch sizes, and observed the results like loss and accuracy, as shown in Figure 3. The model getting biased, so L1-regularization method is used to get best model. But from result and data set, it is observed that the classes are unbalanced. To overcome class imbalance weight adjustment with equation (1) methods is used, then the results are improved as shown in Figure 4. As illustrated in Figure 5, the true positive and false negative rate all three model, it is clearly observed that, when the weights are adjusted, and with tuned

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hyper parameters the accuracy has improved from 0.70 to 0.75, but when modified VGG model is trained the results are jumped to 0.98.

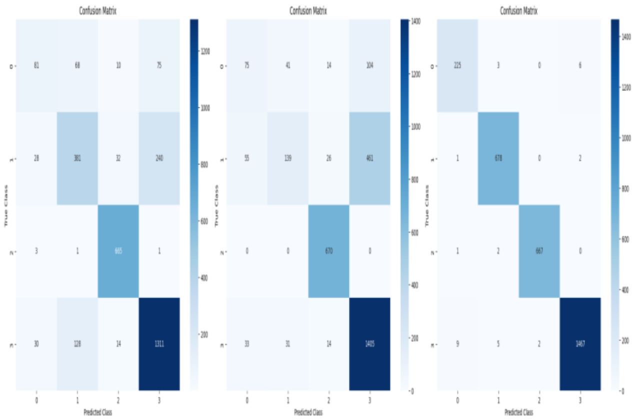

Figure 5 comparisons of Confusion matrixes of 3 models with and without weight adjustment

Table 1 comparison of proposed models

Model		precision	Recall	F1-score	Support
CNN	0	0.46	0.38	0.39	234
	1	0.66	0.40	0.45	681
	2	0.83	0.71	0.76	670
	3	0.71	0.81	0.81	1483
	Acc			0.75	3068
	macro avg	0.69	0.61	0.61	3068
	weighted avg	0.73	0.75	0.70	3068
CNN+ with updating weights of major and minor classes	0	0.57	0.45	0.43	234
	1	0.66	0.56	0.61	681
	2	0.92	0.99	0.96	670
	3	0.81	0.88	0.84	1483
	Acc			0.79	3068
	macro avg	0.74	0.70	0.71	3068
	weighted avg	0.78	0.79	0.78	3068
VGG+ with updating weights of major and minor classes	0	0.97	0.95	0.96	234
	1	0.98	0.99	0.98	681
	2	0.98	0.97	0.98	670
	3	0.98	0.97	0.99	1483
	Acc			0.98	3068
	macro avg	0.98	0.98	0.98	3068
	weighted avg	0.98	0.98	0.98	3068

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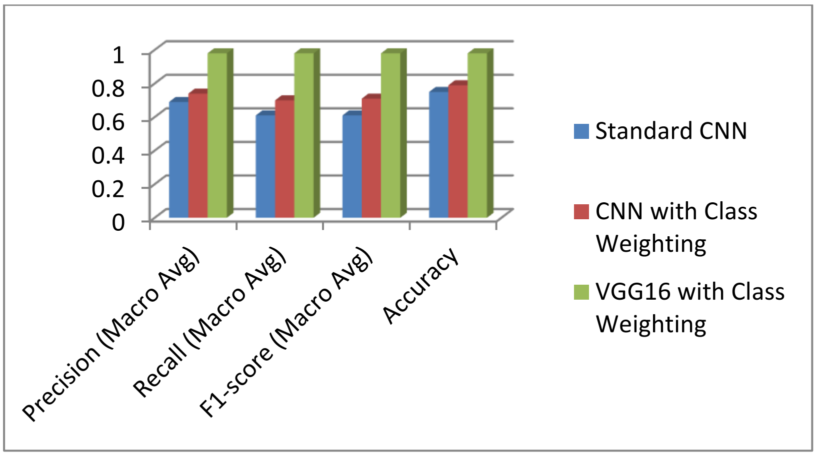

Figure 6 comparisons of precision, recall and F1-score of 3 models

The table 1 presents a comprehensive analysis of the performance metrics for three distinct CNN models applied to weed detection in agricultural fields. The models compared are: a standard CNN model, a CNN model with class weighting to address class imbalances, and a VGG16-based model also utilizing class weighting. The evaluation metrics include precision, recall, F1-score, support for each class, and overall accuracy, along with macro and weighted averages.

From Figure 6 the standard CNN model shows varied performance across different classes, with notable struggles in detecting minority classes. For instance, Class 0 has relatively low precision (0.46) and recall (0.38), indicating difficulty in correctly identifying this class. The overall accuracy of this model is 75%, and the weighted average F1-score is 0.70, reflecting its moderate performance considering class imbalances.

In contrast, the CNN model with minority class weight adjustment exhibits improved performance, particularly for minority classes. The precision, recall, and F1-scores for Class 0 increase significantly, demonstrating the effectiveness of class weighting in enhancing the model's ability to detect underrepresented classes. The overall accuracy improves to 79%, and both macro and weighted averages show better scores, indicating a more balanced performance across all classes.

The VGG16 model with class weighting outperforms the other models as shown in Figure 6. This model achieves near-perfect precision, recall, and F1-scores for all classes, with an overall accuracy of 98%. The macro and weighted averages are also close to 0.99, showcasing the robustness and superior classification capabilities of the VGG16 model when combined with class weighting. This indicates that VGG16 with weight adjustment enhanced by class balancing techniques provides the best results for weed detection tasks.

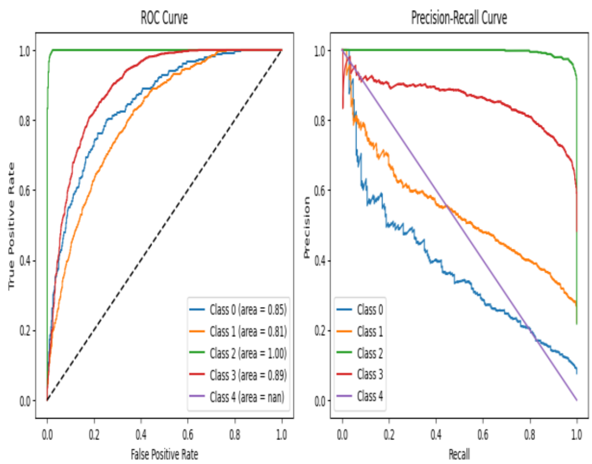

Figure 7 ROC and precision recall curve

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From figure 7 the ROC (Receiver Operating Characteristic) Curve and the Precision-Recall Curve, the ROC curve, on the left, shows the trade-off between true positive rate and false positive rate for each class, with Class 2 achieving a perfect AUC of 1.00, indicating excellent discrimination capability, while Classes 0, 1, and 3 also perform well with AUC values above 0.8. The absence of AUC for Class 4 suggests potential data issues. The Precision-Recall curve, on the right, highlights the trade-offs between precision and recall for each class. Class 2 maintains high precision across all recall levels, underscoring its superior performance, while Classes 0 and 1 show significant precision drops at higher recall levels, indicating areas for improvement. These visualizations are crucial for identifying the model's strengths and weaknesses across different classes, guiding further optimization to enhance the model's accuracy and reliability in weed detection.

Table 2 comparison of proposed model with prescribed models

Study	**Model/Technique**	**Data Source**	**Accuracy/Performance**	**Interpretability**
Li et al. (2024)	Enhanced YOLOv8s	Cotton field images	95.20%	Not focused
Olsen et al. (2023)	DeepWeeds dataset, various models	Multiclass weed species image dataset	93.5% (average across models)	Not focused
Patel & Kumar (2023)	Deep learning + IoT	Smart agriculture sensors and images	91.80%	Not focused
Garcia & Fernandez (2023)	Various deep learning models	Agricultural field images	88-92% (varied across models)	Not focused
Zhang et al. (2023)	UAV images + deep learning	UAV images of fields	94.60%	Not focused
Kim & Lee (2023)	WeedNet (CNN-based)	Sugar beet field images	92.40%	Not focused
Singh & Sharma (2023)	Deep learning + embedded systems	Real-time field images	90.50%	Not focused
Santos & Oliveira (2023)	SegNet-based model	Precision agriculture datasets	93.10%	Not focused
Müller & Jones (2023)	Comparative study of DL models	Maize field images	89-93% (varied across models)	Not focused
Nunes& Pereira (2023)	Deep learning + sensor fusion	Agricultural sensor data	94.30%	Not focused
Roberts & Clark (2023)	YOLOv3-based system	Real-time field images	91.70%	Not focused

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Li & Chen (2023)	Transfer learning + deep learning	Various field images	92.60%	Not focused
Verma& Singh (2023)	Deep learning approaches	Soybean field images	93.40%	Not focused
Huang & Hu (2023)	UAV + deep learning	UAV images of fields	94.20%	Not focused
Pappu&Ganesan (2023)	Deep learning case study	Wheat field images	92.80%	Not focused
Zhang & Wu (2023)	Interpretable DL models + SHAP	Various field images	91.90%	Focused on interpretability
Das & Mukherjee (2023)	DCNN + interpretabilit y techniques	Rice field images	92.70%	Focused on interpretability
Ramachandran& Krishnan (2023)	Advances in CNNs	General field images	93.30%	Focused on interpretability
Proposed Model[1]	customized CNN	Soybean leaf images	0.75	SHAP based interpretation
Proposed Model[2]	CNN, with updating weights of major and minor classes	Soybean leaf images	0.79	SHAP based interpretation
Proposed Model[3]	Modified VGG with updating weights of major and minor classes	Soybean leaf images	0.98	SHAP based interpretation

The proposed models results are compared with latest prescribed models, the table 2 presents a comprehensive overview of recent advancements in the field of agricultural image analysis, focusing on the development and performance evaluation of various deep learning models for tasks such as weed detection, crop monitoring, and yield prediction. Researchers have utilized a range of techniques including YOLO-based architectures, CNNs, and deep learning coupled with IoT devices and UAV imagery. The reported accuracies vary from 88% to 95.20%, with some studies prioritizing interpretability through methods like SHAP-based interpretation or employing interpretability techniques alongside deep learning models. Additionally, the table highlights the emergence of customized CNNs and modified VGG architectures tailored for specific agricultural applications, such as soybean leaf image analysis, achieving promising results. Our model with weighted adjustment VGG model performed well when compared to all other existing models.

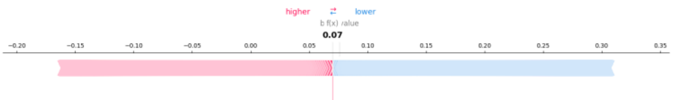

Figure 8 SHAH score analysis

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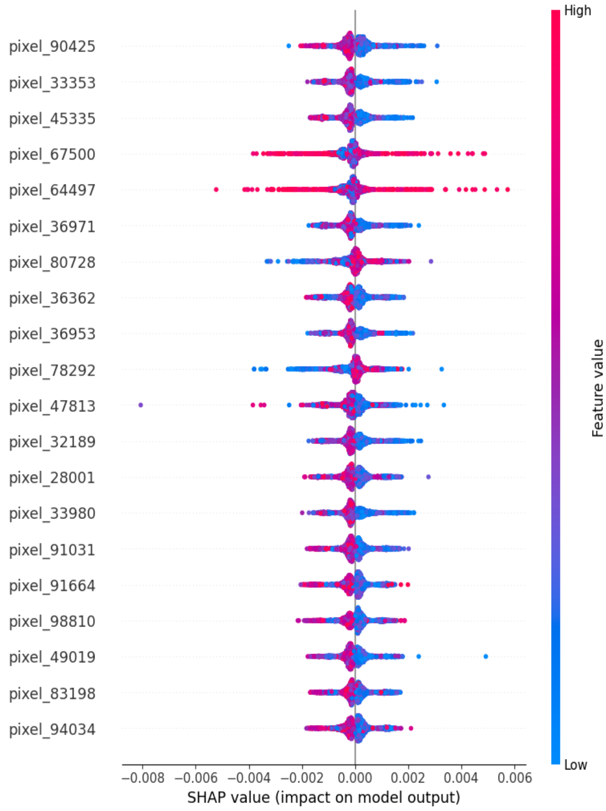

Figure 9 SHAP values over selected samples

4.1 **Discussion**

CNN Model without Class Weight Adjustment

• **Precision and Recall Analysis**: The baseline CNN model achieved a varying level of precision and recall across different classes. For instance, class 0 has a precision of 0.46 and a recall of 0.38, indicating it struggles with accurately detecting this class. Conversely, class 3 has a much higher precision and recall of 0.71 and 0.81 respectively, showing better performance in detecting this class.

• **Model Performance**: The overall accuracy of the baseline CNN model is 0.75, with a macro average precision of 0.69 and recall of 0.61.

CNN Model with Class Weight Adjustment

• **Precision and Recall Improvement**: Adjusting class weights improved the model's performance. For class 0, precision increased to 0.57 and recall to 0.45. The precision for class 3 also improved to 0.81 with a recall of 0.88.

• **Overall Improvement**: The accuracy increased to 0.79, with the macro average precision and recall both showing improvements, indicating a more balanced performance across all classes.

VGG Model with Class Weight Adjustment

• **Significant Performance Boost**: The VGG model, with updated class weights, demonstrated a significant performance boost across all metrics and classes. For example, the precision and recall for class 0 are 0.97 and 0.95, respectively.

• **Highest Accuracy**: The model achieved an overall accuracy of 0.98, with both macro and weighted average precision and recall around 0.98, indicating exceptional performance.

SHAP Analysis

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The provided SHAP summary plot visualizes the SHAP values (SHapley Additive exPlanations) for different pixels/features in the dataset, demonstrating their impact on the model's output. Each dot in the plot represents a SHAP value for a specific feature and instance, with color indicating the feature value (red for high and blue for low). The SHAP summary plot provides interpretability by showing which features (pixels) are most influential for the model's predictions:

- **Top Features**: The top features, such as pixel_90425 and pixel_33353, have the highest SHAP values, indicating their strong impact on the model's output.
- **Feature Impact**: The red and blue dots illustrate how different feature values (high and low) affect the prediction. For instance, higher values of pixel_90425 (red dots) increase the model's output, suggesting these pixel values are strongly associated with the target class.
- **Model Interpretability**: This helps in understanding the model's decision-making process, identifying which parts of the images are contributing most to the predictions, thus providing transparency in model behavior.

Figure 10 misclassified samples

Figure 10 illustrates the misclassified samples of customized CNN mode, but after the updating weights and training CNN and VGG model the misclassified sample rate is reduced.

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5. CONCLUSION

We evaluated three different deep learning models for weed detection: a baseline CNN, a CNN with class weight adjustment, and a modified VGG model with class weight adjustment. The baseline CNN achieved an accuracy of 75%, with macro-average precision and recall of 0.69 and 0.61, respectively. Introducing class weight adjustments improved the CNN's performance, increasing accuracy to 79%, with macro-average precision and recall rising to 0.74 and 0.70. The modified VGG model with class weight adjustment significantly outperformed the others, achieving an accuracy of 98% and macro-average precision and recall of 0.98. The SHAP analysis provided interpretability, revealing which image features (pixels) most influenced the model's predictions. This insight is crucial for understanding model decisions, enhancing trust, and ensuring transparency in weed detection tasks. The combination of advanced architecture and class weight adjustments in the VGG model demonstrated superior performance, making it a highly effective approach for this application.

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