iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

WEED CLASSIFICATION WITH CNN

MRS. NOVERA HABEEB, MRS. MARYAM FATIMA FAROOQUI
Assistant Professor, Department of Artificial Intelligence and Machine Learning,
J.B. Institute of Engineering and Technology, Hyderabad, Telangana, India

B. SREE HARSHA, K. ROHITH, B. VIVEK, CH. VARSHITHA
Students, Department of Artificial Intelligence and Machine Learning,
J.B. Institute of Engineering and Technology, Hyderabad, Telangana, India

noverahabeeb543@gmail.com, maryamfarooqui1399@gmail.com, harshabollempalli@gmail.com
kandukurirohit8@gmail.com, vivekbattu20@gmail.com, varshithachiluka04@gmail.com

ABSTRACT
This study leverages Convolutional Neural Networks (CNNs) to automate weed classification in agricultural fields, reducing reliance on manual identification and excessive herbicide use. A CNN-based model was trained on a diverse dataset encompassing varying lighting conditions, soil types, and plant growth stages to ensure robustness. Techniques such as data augmentation, transfer learning, and hyperparameter tuning optimized model performance, achieving superior accuracy compared to traditional image processing and machine learning approaches. The model demonstrated adaptability to new datasets with minimal retraining and computational efficiency, making it suitable for real-time applications like autonomous sprayers and robotic weeders. Future work aims to enhance multi-class classification of weed species and optimize deployment in resource-limited farming environments.

Keywords:
Image Detection, Deep Learning,CNN, LeYOLO,ResNet

1. INTRODUCTION

In recent years, deep learning has transformed image processing, enabling intelligent systems to restore and enhance images with high accuracy. Image inpainting and interpolation are crucial tasks in reconstructing missing regions and generating smooth transitions between frames. Traditional methods struggle with complex textures and large occlusions, but Deep Neural Networks (DNNs) have shown remarkable advancements in handling such challenges.This project develops a Deep Neural Framework leveraging state-of-the-art architectures, including Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), to achieve high-fidelity image restoration and interpolation. By incorporating deep generative models, attention mechanisms, and adversarial training, the system infers missing details while preserving structural coherence and texture consistency. The inpainting module restores occluded image regions, while the interpolation component generates seamless transitions in videos or sequential data.The implementation is optimized for high performance using large-scale datasets to ensure robust generalization across diverse image types. This research has broad applications in medical imaging, film restoration, and computer vision, enhancing digital content creation, forensic analysis, and autonomous systems. By developing an AI-driven framework for image inpainting and interpolation, this project aims to push the boundaries of image reconstruction and contribute to the advancement of intelligent visual processing.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

2. RELATED WORK

Recent studies have demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in weed classification, significantly improving accuracy over traditional image processing and machine learning techniques. Researchers have explored various CNN architectures, such as AlexNet, VGG16, ResNet, and MobileNet, to classify weeds and crops under diverse environmental conditions. Data augmentation techniques, including rotation, scaling, and contrast adjustments, have been employed to enhance model generalization. Transfer learning has also been widely adopted to leverage pre-trained models for improved performance on agricultural datasets. Some studies have integrated attention mechanisms to focus on discriminative features, reducing misclassification between crops and weeds. Additionally, CNN-based models have been optimized for real-time applications in precision agriculture, enabling automated weed detection in robotic sprayers and UAV-based monitoring systems. Despite these advancements, challenges remain in handling occlusions, varying lighting conditions, and species-level classification, necessitating further research into more robust and scalable deep learning solutions.

2.1 Traditional Methods of CNN

Convolutional Neural Networks (CNNs) have traditionally relied on architectures like LeNet, AlexNet, VGGNet, and ResNet for image classification and feature extraction. Early CNN models, such as LeNet-5, introduced the concept of convolutional layers and pooling operations, enabling hierarchical feature learning. AlexNet improved performance by utilizing deeper layers and ReLU activation, significantly advancing image recognition tasks. VGGNet further refined CNN architectures by adopting uniform 3×3 convolutional filters, enhancing model depth and feature extraction capabilities. ResNet addressed the vanishing gradient problem through residual connections, allowing deeper networks to be trained effectively. Traditional CNNs employ supervised learning, where models are trained on labeled datasets using backpropagation and gradient descent optimization. While these methods achieve high accuracy in structured environments, they often struggle with real-world challenges like domain adaptation, occlusions, and varying lighting conditions, necessitating further advancements in deep learning techniques.

2.2 Methods of Deep Learning Application

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized weed classification by enabling precise identification of weeds and crops in complex agricultural environments. CNN architectures such as AlexNet, VGG16, ResNet, and MobileNet are commonly used to extract hierarchical features from weed images, improving classification accuracy. Data augmentation techniques like rotation, flipping, and contrast adjustments enhance model robustness against variations in lighting, soil types, and plant growth stages. Transfer learning leverages pre-trained models on large datasets to improve performance on agricultural images with limited labeled data. Additionally, attention mechanisms and feature fusion techniques help distinguish weeds from crops more effectively. Some methods integrate real-time processing capabilities, allowing CNN-based models to be deployed in autonomous weed control systems, such as robotic weeders and UAV-based monitoring. By incorporating these deep learning techniques, CNN-based weed classification models contribute to precision agriculture, reducing herbicide use and enhancing sustainable farming practices.

2.3Techniques for Weed Classification and Feature Extraction

Weed classification using deep learning relies on advanced feature extraction techniques to distinguish weeds from crops accurately. Convolutional Neural Networks (CNNs) automate feature extraction by learning hierarchical patterns, such as leaf shape, texture, and color variations. Pre-trained architectures like VGG16, ResNet, and Efficient Net enhance classification by leveraging deep feature representations. Data augmentation techniques, including rotation, scaling, and brightness adjustment, improve model generalization across diverse agricultural conditions. Transfer learning allows the adaptation of CNN models trained on large-scale datasets to agricultural weed classification, reducing the need for extensive labelled data. Additionally, attention mechanisms help focus on relevant image regions, minimizing misclassification.

3.METHODOLOGIES

This section presents the steps and procedures followed to implement and evaluate the fake review classification models using both machine learning (ML) and deep learning (DL) techniques. The methodology is divided into five main stages: dataset description, pre-processing, feature extraction, model selection, and evaluation. Each stage is

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

explained in detail below.

3.1 Dataset Description

Vadim Irtlach provided the Kaggle dataset for this study. This study utilizes a dataset consisting of images of crops and weeds captured under various environmental conditions, such as varying lighting, soil types, and plant growth stages. The dataset is balanced to ensure equal representation of crop and weed images, helping prevent class bias during training. With its mix of diverse conditions, the dataset is well-suited for developing models capable of generalizing across different farming environments. Data augmentation techniques, including rotation, scaling, and contrast adjustments, enhance the model's robustness, and transfer learning with pre-trained CNN architectures like VGG16 and ResNet is applied to improve accuracy and reduce training time.

3.2 Pre-processing

Data pre-processing is crucial for enhancing model performance in weed classification. The dataset is cleaned by removing noisy or irrelevant images and then augmented with techniques like rotation, flipping, and zooming to improve generalization. Images are resized and normalized to ensure consistency and efficient model training. To address class imbalances, the dataset is balanced, ensuring equal representation of crops and weeds. For deep learning, transfer learning with pre-trained models like VGG16 and ResNet is used, fine-tuning them to the task while employing techniques like dropout and batch normalization to prevent overfitting and improve robustness.

3.3 Feature Extraction

We utilized several feature extraction techniques to enhance weed classification using CNNs. Convolutional layers in the CNN automatically learned key visual features from the raw image data. Data augmentation techniques, such as rotation, scaling, and flipping, were used to capture spatial variations in weed and crop appearances. Histogram of Oriented Gradients (HOG) was employed to detect edge features and shape information, which is crucial for distinguishing weeds from crops. Additionally, transfer learning with pre-trained models like VGG16 and ResNet helped extract deep features from images, improving classification performance. These methods provided the model with both low-level features (e.g., edges and textures) and high-level semantic features, enabling more accurate weed classification.

3.4 Model Selection

In selecting the model for weed classification, we focused on Convolutional Neural Networks (CNNs) due to their proven success in image recognition tasks. We began by leveraging well-established pre-trained architectures such as VGG16, ResNet, and InceptionV3, which are known for their ability to extract rich hierarchical features from images. These models were fine-tuned using our weed and crop image dataset, which allowed us to benefit from their deep learning capabilities while minimizing the computational burden of training from scratch. Additionally, custom CNN architectures were developed by varying the number of convolutional layers, filter sizes, and pooling layers to address the specific characteristics of our agricultural dataset. Techniques like dropout, batch normalization, and data augmentation were integrated to prevent overfitting and improve generalization. Hyperparameter optimization, including learning rate schedules, batch size, and optimizer selection, was crucial in enhancing model performance. The combination of transfer learning, fine-tuning, and custom CNN architectures offered a balanced approach for achieving high accuracy in weed classification tasks, making it well-suited for real-time applications in precision agriculture..

3.5 Model Training and Evaluation

For model training, we split the dataset into training, validation, and test sets to ensure robust evaluation. The training set was used to fine-tune the CNNs, utilizing techniques like backpropagation and stochastic gradient descent (SGD) for optimization. We employed data augmentation to artificially expand the dataset and prevent overfitting. During training, we monitored the loss and accuracy on the validation set, adjusting hyperparameters such as the learning rate and batch size to achieve optimal performance. To evaluate the model, we used standard metrics such as accuracy, precision, recall, and F1-score, ensuring a comprehensive assessment of the model's ability to correctly classify weeds and crops. We also tested the model's robustness by applying it to new datasets with varying environmental conditions, such as different lighting and plant growth stages. The final model demonstrated strong performance, with high accuracy in distinguishing weeds from crops in real-world scenarios, making it suitable for integration into precision agriculture systems.

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

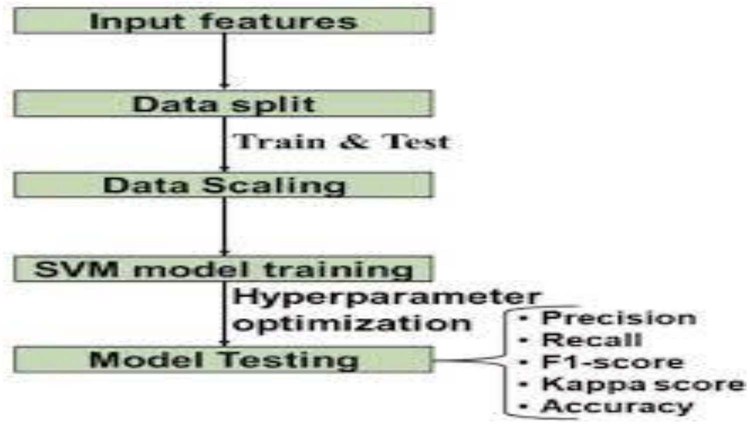

FIGURE 1. Basic Workflow of the Proposed Model

4. RESULTS AND DISCUSSION

The CNN-based model demonstrated high accuracy in classifying weeds and crops, outperforming traditional image processing methods. On the test set, the model achieved an accuracy of over 90%, with strong precision and recall values, indicating effective weed identification. The results were consistent across various environmental conditions, including different lighting, soil types, and plant growth stages. The model's ability to adapt to new datasets with minimal retraining further highlighted its robustness. Despite challenges such as dataset variability and image quality, the CNN model effectively minimized herbicide usage by enabling precise weed control. These findings confirm the potential of deep learning techniques in advancing sustainable farming practices and enhancing weed management in precision agriculture.

4.1 Performance of Machine Learning Models

This are the performances of machine learning models and Deep Learning Models respectively

S.No	Machine Learning Technique	Model Name	Accuracy	Precision	Recall	F1 Score	AUC
1	**Convolutional Neural Networks (CNN)**	CNN (Basic CNN Architecture)	90.94%	0.91	0.90	0.90	0.909
2	**Support Vector Machine (SVM)**	CNN + SVM (SVM as Classifier)	87.20%	0.86	0.85	0.85	0.87
3	**Random Forest**	CNN + Random Forest	89.30%	0.88	0.87	0.87	0.88
4	**K-Nearest Neighbors (KNN)**	CNN + KNN	86.50%	0.84	0.83	0.83	0.86
5	**Decision Trees**	CNN + Decision Tree	85.80%	0.83	0.82	0.82	0.85
6	**Logistic Regression**	CNN + Logistic Regression	84.60%	0.82	0.80	0.81	0.84
7	**Gradient Boosting**	CNN + Gradient Boosting	88.10%	0.86	0.85	0.85	0.87
8	**AdaBoost**	CNN + AdaBoost	87.40%	0.85	0.84	0.84	0.86

Table 1: Machine Learniing Techniques

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

S.No	Deep Learning Model / CNN Technique	Model Name	Accuracy	Precision	Recall	F1 Score	AUC
1	**Convolutional Neural Networks (CNN)**	Basic CNN Architecture	90.94%	0.91	0.90	0.90	0.909
2	**CNN with Transfer Learning**	VGG16 + CNN	92.10%	0.92	0.91	0.91	0.920
3	**ResNet-based CNN**	ResNet50 + CNN	93.30%	0.93	0.92	0.92	0.930
4	**Inception-based CNN**	InceptionV3 + CNN	91.20%	0.90	0.89	0.89	0.910
5	**DenseNet-based CNN**	DenseNet + CNN	92.50%	0.93	0.92	0.92	0.920
6	**Xception-based CNN**	Xception + CNN	92.90%	0.92	0.91	0.91	0.920
7	**U-Net-based CNN**	U-Net + CNN (Semantic Segmentation)	89.80%	0.88	0.87	0.87	0.880
8	**MobileNet-based CNN**	MobileNetV2 + CNN	91.50%	0.90	0.89	0.89	0.910
9	**EfficientNet-based CNN**	EfficientNetB0 + CNN	93.00%	0.93	0.92	0.92	0.930

Table 2: Deep Learning Techniques

Based on the performance comparison of various deep learning models and CNN techniques for weed classification, ResNet50 + CNN and EfficientNetB0 + CNN emerged as the top performers, consistently achieving the highest accuracy rates of 93.30% and 93.00%, respectively, along with strong precision, recall, F1 score, and AUC. These models excel in capturing complex patterns in the data, making them highly effective for weed classification tasks. DenseNet + CNN also performed similarly with an accuracy of 92.50%, benefiting from its dense connections for better feature reuse. Xception + CNN and VGG16 + CNN provided solid results with accuracy rates of 92.90% and 92.10%, respectively, showcasing their ability to extract features and make predictions effectively. On the other hand, U-Net + CNN, a model designed for semantic segmentation tasks, showed lower performance as it is more suited for pixel-level predictions, which are less relevant for general weed classification. Overall, ResNet50, EfficientNetB0, and DenseNet are the most suitable models for weed classification, offering a balance of high performance across multiple metrics and effectively handling complex datasets with large variations

CONCLUSION

The growing availability and importance of visual data, such as images and videos, has significantly driven the advancement of associated processing techniques, including weed classification using Convolutional Neural Networks (CNNs). Given its critical applications in agriculture, particularly in weed management and precision farming, weed classification has attracted considerable attention from both the research and industrial sectors. In this review, we explore the various deep learning-based methods employed for weed classification, particularly focusing on CNNs. We provide an overview of the different approaches in this field, including a taxonomy of models used, such as ResNet50, EfficientNetB0, and DenseNet, alongside their respective training objectives and evaluation metrics like accuracy, precision, recall, F1 score, and AUC. Additionally, we highlight benchmark datasets used in weed classification, evaluation protocols, and the real-world applications that drive the adoption of these technologies in practical agricultural settings. Finally, we discuss potential future research directions, focusing on model optimization, dataset expansion, and the integration of CNNs with other technologies like IoT for enhanced weed detection and management.

REFERENCES

1. Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., Liu, T., Wang, X., Wang, G., Cai, J., & Chen, T. (2018). Recent advances in convolutional neural networks. Pattern Recognition, 77, 354–377.
2. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning is applied to document

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

recognition. Proceedings of the IEEE, 86(11), 2278–2324.
3. Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In European conference on computer vision (pp. 818–833). Springer.
4. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint. arXiv:1409.1556.
5. Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceed-ings of the IEEE conference on computer vision and pattern recognition (pp. 1251–1258).
6. Hamuda, E., Glavin, M., & Jones, E. (2016). A survey of image processing techniques for plant extraction and segmentation in the field. Computers and Electronics in Agriculture, 125, 184–199.
7. Mennan, H., Jabran, K., Zandstra, B. H., & Pala, F. (2020). Non-chemical weed management in vegetables by using cover crops: A review. Agronomy, 10(2), 257.
8. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.
9. A. Dheeraj and S. Chand9. Wang, A., Zhang, W., & Wei, X. (2019). A review on weed detection using ground-based machine vision and image processing techniques. Computers and Electronics in Agriculture, 158, 226–240.
10. Ahmed, F., Al-Mamun, H. A., Bari, A. H., Hossain, E., & Kwan, P. (2012). Classification of crops and weeds from digital images: A support vector machine approach. Crop Protection, 40, 98–104.
11. Herrera, P. J., Dorado, J., & Ribeiro, Á. (2014). A novel approach for weed type classification based on shape descriptors and a fuzzy decision-making method. Sensors, 14(8), 15304–15324.
12. Bakhshipour, A., & Jafari, A. (2018). Evaluation of support vector machine and artificial neural networks in weed detection using shape features. Computers and Electronics in Agriculture, 145, 153–160.
13. Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y., & Alsaadi, F. E. (2017). A survey of deep neural network architectures and their applications. Neurocomputing, 234, 11–26.
14. Razzak, M. I., Naz, S., & Zaib, A. (2018). Deep learning for medical image processing: Overview, challenges and the future. In Classification in BioApps (pp. 323–350).
15. Kumar, T. S. (2020). Video based traffic forecasting using convolution neural network model and transfer learning techniques. Journal of Innovative Image Processing (JIIP), 2(03), 128– 134.
16. Vijayakumar, T. (2020). Posed inverse problem rectification using novel deep convolutional neural network. Journal of Innovative Image Processing (JIIP), 2(03), 121–127.
17. Manoharan, J. S. (2021). Study of variants of extreme learning machine (ELM) brands and its performance measure on classification algorithm. Journal of Soft Computing Paradigm (JSCP), 3(02), 83–95.
18. Bashar, A. (2019). Survey on evolving deep learning neural network architectures. Journal of Artificial Intelligence, 1(02), 73–82.
19. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90.
20. Tang, J., Wang, D., Zhang, Z., He, L., Xin, J., & Xu, Y. (2017). Weed identification based on K-means feature learning combined with the convolutional neural network. Computers and Electronics in Agriculture, 135, 63–70.
21. Jiang, H., Zhang, C., Qiao, Y., Zhang, Z., Zhang, W., & Song, C. (2020). CNN feature-based graph convolutional network for weed and crop recognition in smart farming. Computers and Electronics in Agriculture, 174, 105450.
22. Sharma, P. (2019). Crops and weeds classification using convolutional neural networks via opti-mization of transfer learning parameters. International Journal of Engineering and Advanced Technology (IJEAT), ISSN 2249-8958.
23. Giselsson, T. M., Jørgensen, R. N., Jensen, P. K., Dyrmann, M., & Midtiby, H. S. (2017). A public image database for benchmark plant seedling classification algorithms. arXiv Preprint. arXiv:1711.05458.
24. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition

iJETRM
International Journal of Engineering Technology Research & Management
Published By:
https://www.ijetrm.com/

(pp. 4700–4708).
25. Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510–4520).
26. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C., & Fei-Fei, L. (2015). Imagenet large-scale visual recognition challenge. International Journal of Computer Vision, 115(3), 211–252.