Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 29s (2025)
https://www.jneonatalsurg.com

Comparative Evaluation of CNN Models for Precision Agriculture in Deep Learning-Based Weed Detection

K. Mohanappriya[1], Dr.C. Vennila[2], R.Roshan Joshua[3], A.T.Barani Vijaya Kumar[4]

[1]Assistant Professor, Department of Computer Science and Engineering, Saranathan College of Engineering, Tirchirappalli, India

Email ID: mohanapriya-cse@saranathan.ac.in

[2]Professor, Department of Electronics and Communication Engineering, The Principal, VSB Engineering, College,Karur,India

Email ID: vennila.nitt@gmail.com

[3]Research Scholar, Department of Computer Science and Engineering, Saranathan College of Engineering

Tirchirappalli, India

Email ID: roshancse5439@gmail.com

[4]Assistant Professor, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan University

Tirchirappalli, India

Email ID: baranivj@gmail.com

.Cite this paper as: K. Mohanappriya, Dr.C. Vennila, R.Roshan Joshua, A.T.Barani Vijaya Kumar, (2025) Comparative Evaluation of CNN Models for Precision Agriculture in Deep Learning-Based Weed Detection, *Journal of Neonatal Surgery*, 14 (29s), 354-360

ABSTRACT

Precision agriculture depends on automated weed detection to increase crop output and decrease pesticide use. Deep learning-based methods are useful for identifying weeds in the field. This study compares three sets of convolutional neural networks—Densenet, Resnet, and VGGNet—for the purpose of weed detection. A real-time data set that was recorded by a camera in the field is used to perform these models based on accuracy, precision, and recall. All preprocessing methods for performance metrics are completed. According to these results, Densenet outperforms the other two models in terms of accuracy. These observations aid in choosing the best model for agricultural applications in real time

Keywords: *Weed Detection, Deep Learning, Resnet , Densenet, VGGnet, Precision Agriculture, Computer Vision*

1. INTRODUCTION

A significant obstacle in agriculture is identifying the vast number of weeds that would lower crop yields and increase reliance on herbicides. Weeds compete with crops for resources, which lowers agricultural output. It will impact the essential sunlight, water, and nutrition. The impact of weeds can be reduced by employing five main groups of management strategies: "preventative" (preventing weed establishment), "cultural" (keeping the field clean to reduce the weed seed bank), "mechanical" (using mulching, tilling, and cutting techniques), "biological" (using natural enemies like insects, grazing animals, or diseases), and "chemical" (using herbicides). Despite their success, all techniques have drawbacks, most notably that they are costly, time-consuming, and tedious. Additionally, the implementation of control methods may have negative effects on the ecosystem, soil, animals, plants, or people. Weeds have been identified thus far using a variety of techniques and instruments. Due to the labor-intensive, time-consuming, and inefficient nature of traditional manual weed control approaches, large-scale farming is increasingly depending on chemical herbicides. But excessive pesticide use can be bad for the environment and people's health, thus more precise and long-lasting weed control methods are required. Deep learning-based automated weed detection has garnered attention because to

its potential to improve classification accuracy, reduce the need for herbicides, and boost production[1]. This paper focuses on recent weed detection methods using deep learning approaches. It explores the effectiveness of models such as DenseNet, ResNet, VGGNet, and EfficientNet in weed detection. Additionally, a comparative analysis of these techniques is conducted to determine which model achieves the highest accuracy

2. RELATED WORK

This study compares the efficacy of traditional and AI-based techniques for agricultural weed detection. In large-scale farming, traditional techniques like rule-based image processing and manual weed removal are frequently inefficient and labor-intensive. On the other hand, deep learning models such as DenseNet121, ResNet50, VGG16, VGG19, and EfficientNetV2-B3 provide greater automation and accuracy in weed identification. In order to identify the best effective deep learning model, the study assesses these models using a bespoke weed dataset, examining both their training and validation results. According to the results, DenseNet121 performs better than the other models and has the highest validation accuracy, which makes it the best option for practical agricultural applications[1].

Traditionally, conventional methods have been used to detect weeds in agriculture. However, these approaches have several drawbacks, including high labor costs and inefficiency. In an effort to overcome these limitations, artificial intelligence (AI) has become a potent weed detecting technique. Deep learning and machine learning are the most popular AI methods. Although machine learning approaches and deep learning models typically perform better, this section concentrates on machine learning models, specifically Support Vector Machines (SVMs), and conventional techniques. In machine learning-based methods, SVM is the recommended model since it has shown the best performance in weed detection among the other Machine Learning models.

Conventional method for weed detection

Conventional weed identification techniques are inexpensive to utilize in agricultural machinery and equipment, have low needs on graphics processing units, and require small sample sizes. The Traditional methods are

a. *Scouting by Hand*: Manual scouting: In this age-old technique, weeds are found and identified by visually examining fields. It is labor-intensive and unfeasible for large-scale farms, but it works well for small areas.

b. *Mechanical Weed Control:* Methods such as harrowing and tilling can interfere with the establishment and growth of weeds. However, these techniques can also raise the risk of erosion and disrupt the structure of the soil.

c. *Using Herbicides:* Herbicides are chemical substances that specifically target and destroy weeds. Even while they are useful, they may have unforeseen repercussions like poisoning water sources or hurting beneficial insects. Additionally, herbicide-resistant weed populations may arise as a result of excessive herbicide use. The drawbacks of conventional techniques make it necessary to investigate more effective, focused, and long-lasting strategies for weed identification and management. Here, developments in image processing and artificial intelligence (AI) present encouraging answers.

B. Weed Detection Using Machine Learning model of SVM

The ability of Support Vector Machines (SVMs) to differentiate between crops and weeds using a variety of attributes taken from photos has led to their widespread use in weed detection. achieved accuracy rates ranging from 50% to 95% by classifying crops and weeds using RGB components and morphological cues in conjunction with SVMs and blob analysis[2].

The use of Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) to detect weeds using characteristics like size, color, and form. The study highlights how crucial precise weed identification is to lowering farming expenses and increasing output. Weeds can be efficiently recognized and mapped by combining artificial intelligence techniques like ANN and SVM with image processing methods. The authors point out that autonomous weed control techniques, like robotic weed controllers, can reduce or do away with the need for chemical use, providing a more practical approach to weed management because manual labor is costly.

Support Vector Machines (SVMs), one of these machine learning algorithms, have been employed extensively because of its great accuracy and resilience while working with high-dimensional data. According to studies, SVMs have frequently beaten other machine learning models, sometimes reaching 99% accuracy rates.The reason behind its

- *Feature-Based Classification:* SVMs efficiently categorize crops and weeds using texture, color, and form features that are taken from photos.
- *Greater Generalization:* SVMs are appropriate for agricultural applications where labeled data is hard to come by because they function effectively even with small amounts of training data
- *Kernel function advantage:* In non-linearly separable datasets, the application of npolynomial and Radial Basis Function (RBF) kernels increases classification accuracy.

These studies show how important SVMs are for weed detection in agriculture.

3. PROPOSED WORK -DEEP LEARNING -BASED WEED DETECTION

Deep Learning Models:

This paper focuses on deep learning models, specifically DenseNet-121, ResNet, and VGGNet, which are widely used for image classification and feature extraction. These models play a crucial role in weed detection in agriculture, enabling accurate identification and differentiation between crops and weeds.

A.Densenet121:

Weed detection is essential to precision agriculture because unmanaged weed development can significantly reduce crop yields and increase production expenses. Traditional weed management methods employ chemical pesticides and human labor, both of which have disadvantages in terms of their efficacy and environmental impact. One kind of deep learning method that has gained popularity for automated weed detection is Convolutional Neural Networks (CNNs). In that DenseNet-121 has shown promising results among them due to its ability to reuse features and its efficient learning process [3].The design of DenseNet-121 is built on dense connectivity, in which every layer transfers its features to every layer after it and gets inputs from all layers before it. DenseNet improves learning efficiency by allowing information to flow over several layers, in contrast to typical CNNs where levels function independently. The Densenet121 work includes as

Dense Blocks: By enabling layers to exchange learned features rather than requiring each layer to learn new features alone, dense blocks enhance feature propagation and cut down on pointless calculations.

Bottleneck Layers: Reduce the amount of parameters and increase the computational efficiency of the network by using 1×1 convolutions.

Transition Layers: To manage dimensionality and enhance learning stability, these layers include pooling layers, batch normalization, and 1x1 convolutions.

Growth Rate (k): Indicates the number of new characteristics that each layer adds. DenseNet-121 balances computational expense and performance with a moderate growth rate.

Resnet50

Agricultural research has made substantial use of the deep convolutional neural network ResNet-50 for weed detection because of its strong feature extraction capabilities. It has been shown in numerous studies to be successful in precisely identifying and categorizing weed species, supporting precision agricultural methods. The 50 layers that make up ResNet-50 include convolutional, batch normalization, activation (ReLU), pooling, and fully connected layers [4]. The residual learning framework, which is the main novelty in ResNet, enables the model to train deeper networks without degrading. *Residual Blocks:* Prevent gradient disappearance and degradation by introducing skip (shortcut) connections that avoid specific layers.

Bottleneck layers: In order to decrease the number of parameters and increase computational performance, employ 1x1 convolutions.

Batch Normalization:In order to speed up training and stabilize learning, batch normalization normalizes activations between layers.

Global Average Pooling : By reducing spatial dimensions prior to moving on to fully connected layers, (GAP) enhances generalization.

ResNet-50's capacity to recognize intricate patterns in images makes it a popular choice for agricultural image analysis. In terms of weed detection, it successfully distinguishes weeds from crops by using characteristics including color, texture, and shape.

C .VGG16 and VGG19

Deep convolutional neural networks (CNNs) like VGG-16 and VGG-19 are well known for their capacity to perform well in image classification tasks, including weed detection in agricultural applications[6].

There are 16 layers in VGG-16 and 19 layers in VGG-19. Both architectures make use of tiny 3x3 convolutional filters and are renowned for their consistent design, which makes it easier to extract features from photos. They may be used to differentiate weeds from crops because of their capacity to extract hierarchical information from photos, which aids farmers in implementing automated weed control methods. More intricate traits, like weed-crop boundaries and delicate leaf textures, are captured by deeper networks (VGG-19).

Because VGG-16 is more computationally efficient, it can be used in real-time weed identification systems that use edge devices or drones.

VGG-16 is frequently chosen for transfer learning since it maintains good accuracy while training more quickly and using fewer resources.[12]

D.EfficientnetV2-B3:

Recent studies have investigated the potential of EfficientNetV2-B3, a version of the EfficientNetV2 family, for weed detection in agricultural environments. This model is renowned for striking a compromise between computational efficiency and accuracy, which qualifies it for real-time precision agriculture applications.

A popular deep learning model for image classification applications, such as weed identification in agriculture, is EfficientNetV2-B3, which is both lightweight and effective. This enhanced version of EfficientNetV1 aims to increase accuracy while lowering processing costs. In precision agriculture, this model is very helpful for real-time weed detection, which enables better decision-making.

For effective and precise image classification, including weed detection, EfficientNetV2-B3 is composed of several optimized layers. For the initial feature extraction, a 3x3 convolutional stem layer is employed. In the early stages, Fused-MBConv blocks are used, which mix standard and depthwise convolutions for quicker training. Squeeze-and-Excitation (SE) layers in MBConv blocks improve feature selection by readjusting channel priority as the network gets deeper. These blocks employ expansion, depthwise convolution, and projection layers to effectively extract deep features, and their complexity increases gradually. In order to identify images as either crops or weeds, a fully connected (FC) layer with a softmax activation function is used after feature maps have been compressed into a single vector using a Global Average Pooling (GAP) layer [7]. For real-time agricultural applications, EfficientNetV2-B3 is the perfect option because of its combination of Fused-MBConv and SE blocks, which increase model efficiency, lower computing costs, and improve classification accuracy.[13]

4. WORKFLOW OF WEED DETECTION

This study utilizes a **weed dataset** created by capturing images from agricultural fields. The images undergo **preprocessing steps,** including **resizing, normalization, and data augmentation**, to ensure they are in a **properly labeled format** suitable for deep learning models. Once the dataset is prepared, **a pretrained model is** applied, followed by **hyperparameter tuning** for each selected model to optimize performance. The training process is visualized using **heatmaps and colormaps**, allowing for better understanding of feature learning. After training, the model's accuracy is evaluated through **testing and validation.** Finally, a **performance comparison** of different models is conducted by plotting accuracy and loss graphs, providing insights into the most effective approach for weed detection.

a. Dataset Creation : The weed dataset was created by capturing images from agricultural fields using high-resolution cameras. These images were carefully collected under varying lighting and environmental conditions to ensure diversity in the dataset. A sample of this dataset is presented here, illustrating the different weed species identified for detection and classification

b. Dataset Preprocessing: In order to improve model robustness and performance, the dataset is exposed to in Fig 1 as

Resizing: Images are downsized to 224 x 224 pixels, or the pixel size required by models such as ResNet, DenseNet-121, etc.

Normalization: To promote convergence and stabilize training, pixel values are scaled to the interval [0,1].

Augmentation: Increasing dataset diversity and avoiding overfitting can be achieved by data augmentation, which includes: Rotation (±30°) , Zooming (10–20%) , Flipping (horizontal/vertical) ,Contrast modifications ,The infusion of Gaussian noise After the images have been preprocessed, they are classified into different categories (such as "weed" versus "crop") to provide a structured dataset that is prepared for model training.[11]

B.Model Selection and Hyperparameter Tuning

A variety of deep learning models, such as DenseNet-121, ResNet-50, VGG16, and EfficientNet, are assessed in order to get peak performance. In order to determine the optimal set of parameters, hyper parameter tuning is carried out utilizing methods like Grid Search or Bayesian optimization. The Best combination of parameters are

Learning Rate (0.0001 - 0.01): Regulates gradient descent weight updates. The number of images processed per iteration is determined by the *batch size* (16, 32, 64).

Convergence analysis was used to adjust the *number of epochs* (50–200).

Fig 1. Dataset Preprocessing

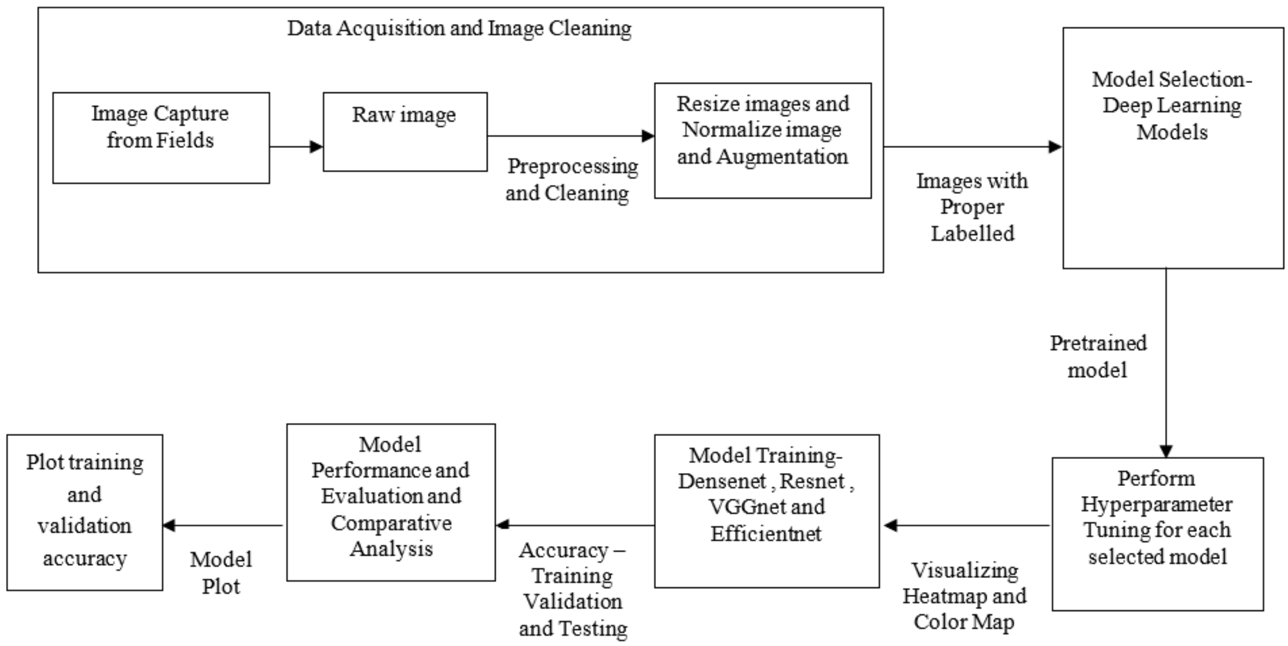

Fig 2. Workflow Diagram

Based on stability and performance, the optimizer (Adam, SGD, RMSprop) was chosen.

• *Dropout Rate* (0.2 - 0.5): Randomly deactivates neurons to avoid overfitting.

C. Training Models and Visualizing Features

For quicker computing, the models are trained utilizing GPU acceleration (e.g., NVIDIA Tesla, RTX) after the hyperparameters have been adjusted. Visualization tools like heatmaps and colormaps aid in the analysis of areas of the input images used for feature extraction. The role that activation layers have in decision-making and the study of gradient flow, guaranteeing steady backpropagation. The **performance metrics** are evaluated by calculating the model's **accuracy** and conducting a **comparative analysis** of

accuracy and loss across epochs. This analysis helps visualize the **model's learning progression** and identifies potential issues such as **overfitting or underfitting**, ensuring optimal performance in weed detection.

5. RESULTS AND DISCUSSION

The deep learning models **DenseNet121, ResNet50, VGG16, VGG19, and EfficientNetV2-B3** have been utilized for weed detection using a dataset created by capturing images from agricultural fields. Following **preprocessing steps** such as resizing, normalization, and augmentation, these models were trained and tested to evaluate their performance. Accuracy was calculated based on **epochs**, and a comparative analysis was conducted to determine the best-performing model. Among them, **DenseNet121 achieved the highest accuracy**, indicating its superior ability to extract intricate features and generalize well for weed classification.

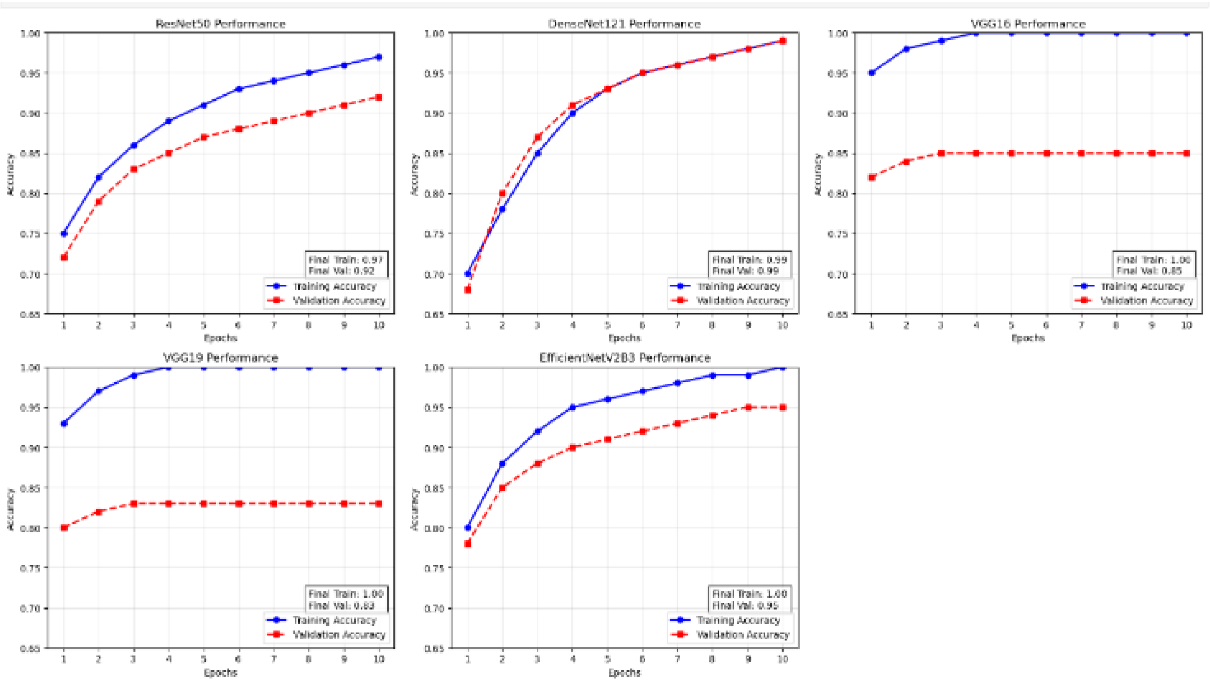

Fig 3.Comparative Performance of Deep Learning Models

The following table presents the accuracy comparison of each model for training and validation, demonstrating the efficiency of DenseNet121 in weed detection tasks. The table shows the DenseNet121 achieved the highest validation accuracy (0.97), making it the best-performing model for weed detection compared to VGG16, VGG19, and EfficientNetV2-B3 reached perfect training accuracy (1.00), but their validation accuracy was lower, indicating potential overfitting and ResNet50 and EfficientNetV2-B3 showed similar validation accuracy (0.91), but ResNet50 had slightly lower training accuracy has shown in Table 1.

Model	Training Accuracy	Validation Accuracy
ResNet50	0.97	0.91
DenseNet121	0.99	0.97
VGG16	1.00	0.85
VGG19	1.00	0.83
EfficientNetV2-B3	1.00	0.91

Table 1 Comparison of Model Performance

6. CONCLUSION

In order to detect weeds in agricultural fields, this study used deep learning models like DenseNet-121, ResNet-50, VGG-16, VGG-19, and EfficientNetV2-B3. Real-time image capture was used to build the dataset, which was then preprocessed using augmentation, normalization, and scaling. Accuracy, loss, and other performance indicators were used to train, test, and assess the models. DenseNet-121 outperformed the other models in terms of accuracy, proving that it is capable of extracting fine-grained features for the classification of weeds. These models' performance shows that deep learning-based strategies perform noticeably better than conventional weed detection techniques, offering precision agriculture an effective alternative. For better feature extraction and lightweight edge AI deployment for real-time weed detection, future research can concentrate on hybrid deep learning models. With little labeled data, classification accuracy can be improved by combining self-supervised learning with multi-spectral photography. Furthermore, by allowing for focused herbicide delivery, weed growth stage classification helps maximize precision agriculture.

REFERENCES

[1] Nafeesa Yousuf Murad,Tariq Mahmood et.al 1Weed Detection Using Deep Learning: A Systematic Literature Review". Sensors 2023, 23, 3670. https://doi.org/ 10.3390/s23073670

[2] Faisal Dharma Adhinata, Wahyono Raden Sumiharto a, "A Comprehensive Survey on Weed and Crop Classification Using Machine Learning" journal homepage: http://www.keaipublishing.com/en/journals/artificialintelligence-in-agriculture/ https://doi.org/10.1016/j.aiia.2024.06.005

[3] Yemu et.al,"DenseNet Weed Recognition Model Combining Local Variance Preprocessing and Efficient Channel Attention Mechanism"Front. Plant Sci. , 12 January 2023Sec. Sustainable and Intelligent Phytoprotection Volume 13 - 2022 | https://doi.org/10.3389/fpls.2022.1041510

[4] Kun Hu , Guy Coleman , Shan Zeng , Zhiyong Wang , Michael Walsh,"Graph Weeds Net: A Graph-Based Deep Learning Method for Weed Recognition"Computers and Electronics in Agriculture Volume 174, July 2020, 105520, https://doi.org/10.1016/j.compag.2020.105520

[5] Oscar Leonardo García-Navarrete, Adriana Correa-Guimaraes and Luis Manuel Navas-Gracia"Application of Convolutional Neural Networks in Weed Detection and Identification: A Systematic Review"Agriculture 2024, 14, 568. https://doi.org/10.3390/ agriculture14040568

[6] Xiaojun Jin, Muthukumar Bagavathiannan, Patrick E McCullough, Yong Chen et.al"A Deep Learning-Based Method for Classification, Detection, and Localization of Weeds in Turfgrass"https://scijournals.onlinelibrary.wiley.com/doi/epdf/10.1002/ps.7102, 28 July 2022 https://doi.org/10.1002/ps.7102

[7] A Dheeraj, S Marwaha, S Nigam, MA Haque, Madhu,"ADNet: An Attention Embedded DenseNet121 Model for Weed Classification in Maize Crop"Springer Nature Switzerland AG 2024D. Pastor-Escuredo et al. (Eds.): ICDLAIR 2023, LNNS 1001, pp. 626–638, 2024.https://doi.org/10.1007/978-3-031-60935-0_55

[8] Zhuolin Li , Dashuai Wang , Qing Yan, Minghu Zhao , Xiaohu Wu , Xiaoguang Liu "Winter Wheat Weed Detection Based on Deep Learning Models"Computers and Electronics in Agriculture.,Volume 227, Part 1, December 2024, 109448, www.sciencedirect.com https://doi.org/10.1016/j.compag.2024.109448

[9] Marios Vasileiou a, Leonidas Sotirios Kyrgiakos a , Christina Kleisiari et.al Transforming Weed Management in Sustainable Agriculture with Artificial Intelligence: A Review" Contents lists available at ScienceDirect Crop Protection journal homepage: www.elsevier.com/locate/cropro https://doi.org/10.1016/j.cropro.2023.106522

[10] A S M Mahmudul Hasan, Ferdous Sohel, Dean Diepeveen, Hamid Laga, Michael G.K. JonesWeed Recognition using Deep Learning Techniques on Class-imbalanced ImageryCrop & Pasture Science, 74(6), 628–644. doi:10.1071/CP21626

[11] Palanisamy R, Gnana Kousalya C, Ramkumar R, Usha S, Thamizh Thentral TM, D Selvabharathi, Shanmugasundaram V,Analysing UPQC performance with dual NPC converters: Three-dimensional and two-dimensional space vector modulation, Results in Engineering,Volume25,2025,103611,ISSN25901230.

[12] Chandrasekar, L.B., Ramkumar, R., Kiruba, S. et al. The Influence of Bi Doping Concentration on Structural, Dielectric and Optical Properties of Bi-doped ZnO thin Films. Semiconductors 59, 61–69 (2025). https://doi.org/10.1134/S1063782624602127

[13] Geetha, A., Usha, S., Padmanabhan, J.B., Palanisamy, R., Alexander, A., Peter, G.,Ramkumar, R., Ganji, V.: Performance evaluation of coloured filters on PV panels in an outdoor environment. IET Renew. Power Gener. 1– 23 (2024). https://doi.org/10.1049/rpg2.13040