Journal of Information Systems Engineering and Management
2024,9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

A Hybrid Deep Learning Approach for Cotton Weed Classification

Himabindu Cheruku[1], Dr. Vemuri Madhukar[2]*
[1]Research Scholar, Department of Computer Science, Chaitanya (Deemed to be University), Himayatnagar, Telangana,500075
[2]Associate Professor, Department of Computer Science, Chaitanya (Deemed to be University), Himayatnagar, Telangana,500075
***Corresponding Author:** Dr. Vemuri Madhukar
*Email: vmadhukar@chaitanya.edu.in

ARTICLE INFO

Received:15 Aug 2024
Revised: 10 Sept 2024
Accepted: 20 Oct 2024

ABSTRACT

Cotton is crucial; effective weed management ensures its yield and quality. Conventional weed control methods, especially herbicides, have led to herbicide resistance and environmental concerns. This study introduces a novel hybrid deep learning network named Shepard Convolutional Fuzzy ShuffleNet (ShCFShuffleNet) for cotton weed classification. The methodology involves preprocessing input images using a Kalman filter, segmenting weeds with Psi-Net, augmenting data with shearing and random erasing, and extracting features for classification. The ShCFShuffleNet integrates Shepard Convolutional Neural Network (ShCNN) and ShuffleNet with fuzzy concepts to improve accuracy. The proposed approach achieves superior performance with precision, Sensitivity, and specificity of 91.3%, 90%, and 92.7%, respectively.

Keywords: Cotton weed classification, Kalman filter, Shepard convolutional neural network (ShCNN), ShuffleNet, Psi-Net.

1. INTRODUCTION

Weeds threaten cotton production by impeding agricultural equipment and competing with crops for nutrients. Herbicide resistance and environmental issues result from heavily relying on herbicides in traditional weed control methods. The challenge of accurate weed recognition in unstructured field conditions necessitates the development of advanced deep-learning techniques. Convolutional neural networks (CNNs), in particular, have demonstrated recent breakthroughs in deep learning. Promising results in agricultural applications, including weed classification. This research proposes a hybrid deep learning model, ShCFShuffleNet, for accurate cotton weed classification.
Agriculture plays a vital role in ensuring food security and economic stability worldwide. Cotton is one of the most significant cash crops. Still, its production faces challenges due to weed infestation, which competes with the crop for nutrients, sunlight, and water, reducing yield and quality(Rale et al. 2019). Traditional weed management approaches rely heavily on chemical herbicides, which have led to herbicide-resistant weed species and pose environmental risks, including soil degradation and water contamination(Chen et al. 2013).
Recent advancements in artificial intelligence (AI) and deep learning (DL) have revolutionized agricultural practices, providing efficient solutions for automatic weed detection and classification (Jin, Che, and Chen 2021). Convolutional Neural Networks (CNNs) have shown promising results in farm applications, including plant disease identification and weed classification, due to their ability to learn complex patterns from image data(Olsen et al. 2019). However, existing models suffer from limitations such as high computational costs, Sensitivity to environmental variations, and difficulty distinguishing visually similar weed and crop species(Deva Kumar et al. 2023).
To address these challenges, this study proposes a hybrid deep learning model, Shepard Convolutional Fuzzy ShuffleNet (ShCFShuffleNet), which integrates Shepard Convolutional Neural Network (ShCNN) and ShuffleNet. This hybrid approach enhances feature extraction and classification accuracy by incorporating fuzzy logic, which refines decision-making processes (Manikandakumar and Karthikeyan 2022). The model also employs preprocessing techniques such as Kalman filtering for noise reduction and Psi-Net for weed segmentation, followed by data augmentation techniques to improve generalization.

Journal of Information Systems Engineering and Management
2024,9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

The primary contributions of this study include:

- Development of a novel hybrid deep learning model (ShCFShuffleNet) for cotton weed classification.
- Integration of fuzzy logic concepts to enhance classification accuracy.
- Utilization of advanced image processing techniques for noise reduction and weed segmentation.
- Performance evaluation against state-of-the-art models, demonstrating improved accuracy, Sensitivity, and specificity.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 details the methodology, including preprocessing, feature extraction, and classification. Section 4 discusses experimental results and comparative analysis. Finally, Section 5 concludes the study and suggests future research directions.

2. RELATED WORK

Several deep learning-based methods have been employed for weed detection, including InceptionV4, Xception, Deep Convolutional Neural Networks (DCNNs), CenterNet, and Mask R-CNN. While these methods have demonstrated significant improvements in weed classification, they face limitations such as high computational cost, overfitting, and difficulty in generalization. The proposed ShCFShuffleNet addresses these limitations by integrating ShCNN and ShuffleNet while incorporating fuzzy logic for enhanced classification.

Several deep learning-based methods have been employed for weed detection, showcasing significant classification accuracy and robustness advancements.

(Hasan et al. 2023) introduced a patch-based deep learning approach for crop and weed recognition, demonstrating high weed detection accuracy. However, the method was limited by high computational cost and patch selection constraints. (Deva Kumar et al. 2023) proposed an InceptionV4-Xception-based model that improved retraining efficiency but required specialized hardware and trained personnel for implementation.

(Yu et al. 2019) developed a deep convolutional neural network (DCNN) for ground-based weed detection, effectively classifying weeds in Bermuda grass. However, overfitting was a notable challenge, restricting the model's ability to generalize to unseen data. (Chen et al. 2013) introduced CenterNet, which proved effective for ground-based weed recognition in vegetable plantations but was not optimized for real-time video analysis. (Sapkota et al. 2022) used Mask R-CNN with real photos to lower the training data needed for weed detection. However, its efficacy in different weed densities was restricted due to the lack of extra training samples. (Moazzam et al. 2023) proposed a W-shaped convolutional network that performed exceptionally well in classifying weeds, although it was not validated on a variety of crop species.

These investigations demonstrate the necessity of a deep learning model optimized to tackle the problems of real-time weed classification, generalizability, and computational economy. The proposed ShCFShuffleNet aims to address these shortcomings and enhance feature learning and classification accuracy by combining Shepard CNN and ShuffleNet with fuzzy logic.

3. PROPOSED METHODOLOGY

The ShCFShuffleNet framework consists of several stages: preprocessing, weed segmentation, data augmentation, feature extraction, and classification.

Journal of Information Systems Engineering and Management
2024,9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

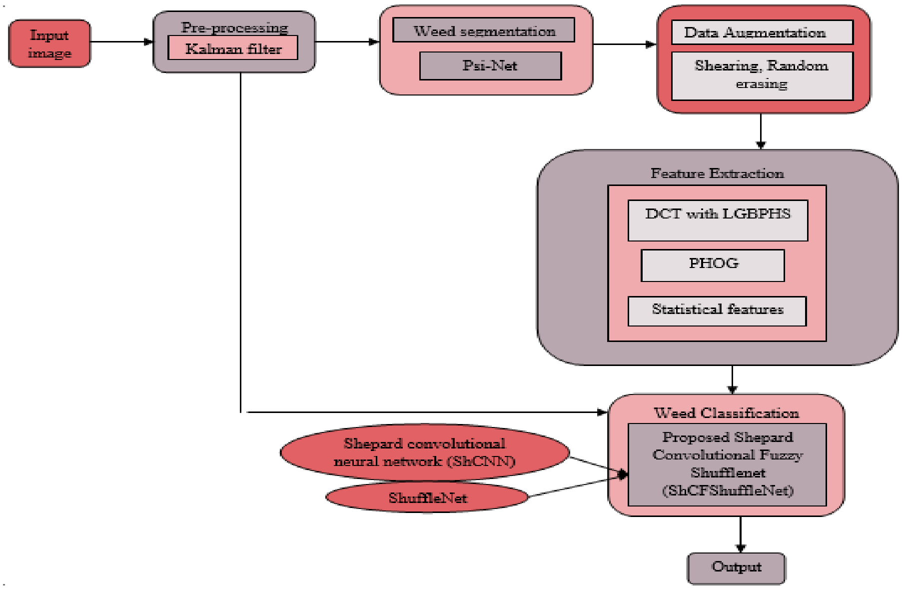

Fig 1. Pictorial view of ShCFShuffleNet for Cotton Weed classification

3.1 Preprocessing

Kalman filter is used for noise reduction and image enhancement. The filtered image serves as input for further processing.

3.2 Weed Segmentation

Psi-Net, a deep learning segmentation network, separates weeds from the backdrop to provide precise weed localization.

3.3 Data Augmentation

- Two techniques are applied to increase the training dataset:
- **Shearing**
- **Random Erasing**

3.4 Feature Extraction

Key features such as Discrete Cosine Transform (DCT) with Local Gabor Binary Pattern Histogram Sequence (LGBPHS), Pyramid Histogram of Oriented Gradients (PHOG), and statistical features (mean, variance, kurtosis, skewness, and standard deviation) are extracted for classification.

- The segmented images are used to extract a variety of features:
- Discrete Cosine Transform (DCT) with Local Gabor Binary Pattern Histogram Sequence (LGBPHS)
- Pyramid Histogram of Oriented Gradients (PHOG)
- Statistical features include mean, variance, kurtosis, skewness, and standard deviation.

3.5 Classification using ShCFShuffleNet

The classification stage employs ShCFShuffleNet, which combines ShCNN and ShuffleNet. ShCNN incorporates Shepard interpolation to improve feature learning, while ShuffleNet enhances computational efficiency. The fusion layer integrates extracted features, and fuzzy logic is applied to refine classification boundaries.

- The **ShCFShuffleNet** model is used for classification, which is a hybrid of:
- **Shepard Convolutional Neural Network (ShCNN)**
- **ShuffleNet**
- The layers of **ShCFShuffleNet** are further enhanced using **fuzzy concepts**.

Journal of Information Systems Engineering and Management
2024,9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

4. EXPERIMENTAL RESULTS

4.1 Dataset

The CottonWeedDet3 dataset, comprising 848 RGB images of three weed types, is used for evaluation alongside bounding box annotations (.json), which are common in cotton fields in the southern U.S. states. These images were acquired by either smartphones or hand-held digital cameras under natural field light conditions and at varied weed growth stages. The annotations (.json) comply with the structure of the VIA JSON File. The dataset assessed a set of one-stage and two-stage deep-learning object detectors. Images are captured under varying lighting conditions using digital cameras and smartphones.

4.2 Performance Metrics

The metrics used for ShCFShuffleNet are determined as follows.

4.4.1 Accuracy

The(Muhammad et al. 2020) overall probability, where the approach well classifies a patient by,

$$\boxed{Acc = \frac{TP + TN}{TP + TN + FP + FN}} \quad (1)$$

4.4.2 Sensitivity

It (Muhammad et al. 2020) is the ratio of accurate classification to the actual positive values that is specified as,

$$\boxed{Sen = \frac{TP}{TP + FN}} \quad (2)$$

4.4.3 Specificity

It(Muhammad et al. 2020) is the ratio of negative results accurately classified by the module that is formulated,

$$\boxed{Spec = \frac{TN}{TN + FP}} \quad (3)$$

Actual positive, true negative, false positive and false negative impl TP, TN, FP, FN y.

4.4.4 ROC

The ROC curve is based on the actual positive rate (TPR) and false positive rate (FPR) at every threshold setting.

4.3 Comparative Analysis

The **comparative analysis** of **ShCFShuffleNet** against existing methods, including **InceptionV4+Xception, DCNN, CenterNet, and Mask R-CNN**, demonstrates its superior performance in **cotton weed classification**. The evaluation is conducted using **accuracy, Sensitivity, and specificity** metrics. In Table 1, the comparative value of ShCFShuffleNet is mentioned. In this module, the accuracy of the proposed ShCFShuffleNet gained 91.3%, which is more than the existing techniques, namely, InceptionV4+Xception, DCNN, CenterNet and Mask R-CNN. This shows that the proposed module can diminish herbicides' usage. The Sensitivity of the proposed ShCFShuffleNet was observed at 90% when compared with conventional modules. This enumerates that the proposed ShCFShuffleNet has the highest value in Sensitivity, which allows for earlier prediction of weeds that enables the farmers to consider quick action before it spreads and is made difficult. The specificity of ShCFShuffleNet was observed at 92.7%, which diminishes the effect on non-target organisms and environmental harm risk and conserves ecosystem balance. Overall, the performance metrics employed for ShCFShuffleNet are effective in lessening environmental impact and are helpful in sustainable agriculture practices.

Table 1. Comparative Discussion

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
InceptionV4+Xception	84.9	84.1	85.7
DCNN	85.1	85.0	86.4
CenterNet	85.4	87.8	89.1
Mask R-CNN	88.1	87.8	89.9
Proposed ShCFShuffleNet	**91.3**	**90.0**	**92.7**

Existing techniques such as InceptionV4+Xception, DCNN, CenterNet, and Mask R-CNN are contrasted with ShCFShuffleNet. The suggested strategy performs better than these techniques, with more specificity (92.7%), Sensitivity (90.0%), and accuracy (91.3%).

5. CONCLUSION

This research presents ShCFShuffleNet, a novel hybrid deep-learning model for cotton weed classification. By integrating Shepard CNN and ShuffleNet with fuzzy concepts, the proposed approach achieves superior classification performance compared to existing methods. Future work will explore using high-resolution satellite and drone-based imagery for large-scale cotton weed monitoring. In modern precision agriculture, accurate weed classification is essential for optimizing crop yield and minimizing herbicide usage. This research introduced ShCFShuffleNet, a hybrid deep learning model combining Shepard CNN (ShCNN) and ShuffleNet with fuzzy layer modifications to enhance classification accuracy. The Kalman filter removes noise, and Psi-Net effectively segments weeds from crops.
Utilizes DCT with LGBPHS, PHOG, and statistical features for superior classification.
Outperforms traditional methods (InceptionV4+Xception, DCNN, CenterNet, and Mask R-CNN) with 91.3% accuracy, 90.0% sensitivity, and 92.7% specificity.

REFERENCES:

[1] Chen, Yong et al. 2013. “Intra-Row Weed Recognition Using Plant Spacing Information in Stereo Images.” *American Society of Agricultural and Biological Engineers Annual International Meeting 2013, ASABE 2013* 2(January 2013): 915–21.

[2] Deva Kumar, I., J. Sai Rashitha Sree, M. Devi Sowmya, and G. Kalyani. 2023. “Precision Agriculture with Weed Detection Using Deep Learning.” *Lecture Notes in Networks and Systems* 494(March): 455–63.

[3] Hasan, A. S.M.Mahmudul et al. 2023. “Image Patch-Based Deep Learning Approach for Crop and Weed Recognition.” *Ecological Informatics* 78(October): 102361. https://doi.org/10.1016/j.ecoinf.2023.102361.

[4] Jin, Xiaojun, Jun Che, and Yong Chen. 2021. “Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation.” *IEEE Access* 9: 10940–50.

[5] Manikandakumar, M., and P. Karthikeyan. 2022. “Weed Classification Using Particle Swarm Optimization and Deep Learning Models.” *Computer Systems Science and Engineering* 44(1): 913–27.

[6] Moazzam, Syed Imran et al. 2023. “A W-Shaped Convolutional Network for Robust Crop and Weed Classification in Agriculture.” *Precision Agriculture* 24(5): 2002–18. https://doi.org/10.1007/s11119-023-10027-7.

[7] Muhammad, Yar, Muhammad Tahir, Maqsood Hayat, and Kil To Chong. 2020. “Early and Accurate Detection and Diagnosis of Heart Disease Using Intelligent Computational Model.” *Scientific Reports* 10(1): 1–17. https://doi.org/10.1038/s41598-020-76635-9.

[8] Olsen, Alex et al. 2019. “DeepWeeds: A Multiclass Weed Species Image Dataset for Deep Learning.”

2024,9(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Scientific Reports 9(1): 1–12. http://dx.doi.org/10.1038/s41598-018-38343-3.

[9] Rale, Neha et al. 2019. “Prediction of Crop Cultivation.” *2019 IEEE 9th Annual Computing and Communication Workshop and Conference, CCWC 2019*: 227–32.

[10] Sapkota, Bishwa B. et al. 2022. “Use of Synthetic Images for Training a Deep Learning Model for Weed Detection and Biomass Estimation in Cotton.” *Scientific Reports* 12(1): 1–18. https://doi.org/10.1038/s41598-022-23399-z.

[11] Yu, Jialin, Shaun M. Sharpe, Arnold W. Schumann, and Nathan S. Boyd. 2019. “Deep Learning for Image-Based Weed Detection in Turfgrass.” *European Journal of Agronomy* 104(October 2018): 78–84. https://doi.org/10.1016/j.eja.2019.01.004.