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Intelligent Weed Detection for Sustainable Agriculture Using Deep Learning

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Abstract- It is a study to create intelligent farming technology in sustainable weed classification by using a self-operated device that utilises image processing and CNN in proper classification. The system can deploy in real time, making use of the chemical less while easing farm functions. Through lesser use of herbicide, it minimises contamination of soil and water, defending human health as well as non-pesticidal insects, and encouraging natural methods of weeding. Moreover, precision fertilizer management reduces expenses, making sustainable agriculture more feasible. The model combines environmental protection with farm productivity, leading to a robust food supply chain. The model attains 99.3% accuracy, 99% precision, recall, F1 score, and weighted average of 600 for support with visualized performance graphs.

Indexed Terms— CNN (Convolutional Neural Network), Accuracy, Precision, Recall, F1 Score, machine learning, Image processing.

I. INTRODUCTION

Agriculture is an important sector that sustains the world economy, but unmanaged weed growth greatly affects crop yields and quality. Weeds compete for nutrients, water, and sunlight with crops, thus reducing yields and raising production costs. Conventional methods of weed control, including hand pulling, plowing, and the use of too many herbicides, are labor-intensive, time-consuming, and destructive to the environment. The excessive application of herbicides is responsible for soil erosion, water pollution, herbicide resistance, and loss of biodiversity, constituting serious risks to sustainable agriculture. Moreover, shortages of labor and increasing operating costs render traditional weed management techniques less feasible for large-scale agricultural farming.

With recent developments in artificial intelligence, machine learning methods have become popular in precision agriculture for autonomous weed detection and elimination. This study suggests an AI-based weed identification system using deep learning, namely a ResNet-101 CNN architecture, and sophisticated image processing methods like segmentation and feature extraction. The system is intended to identify crops and different types of weeds with high accuracy even under varying environmental conditions. By incorporating a wide agricultural dataset including images of varied locations, types of soil, and weather patterns, the system provides reliability under real-world implementations. The online nature of the system provides opportunities for real-time weed identification and action, further minimizing labor expenditure and improving the overall efficiency in farming.

In addition, the algorithm the model includes uses a number of global pooling and a tensor reshaping techniques which allows the model to be universally valid across a wide spectrum of weed species and environmental scenarios. The learning process that is carried out repeatedly makes the model's parameters better over several training epochs, hence fewer classification errors and the accuracy progressing. Its adaptation ability to the weed species that are not described in the system and agrarian spaces that have been evolving is enough to make it reasonable for worldwide farmers to use. The system that continues to learn from the new data can, in time, exhibit the best performance that is both efficient and sustainable, and simultaneously fit into the different agricultural environments

Figure 1 Weed Image

Through the combination of deep learning with real-time image processing, the system offers an effective, self-sustaining weed detection solution that minimizes reliance on chemical herbicides, decreases operational costs, and improves crop yields. Selective detection of weed types allows for specific intervention, averting indiscriminate spraying of herbicides and facilitating green farming techniques. Implementation of such AI-powered precision agriculture systems leads to sustainable food production, environmental protection, and long-term agricultural sustainability.

Apart from the detection of weeds, the architecture of the system can be augmented to other agri-applications like plant disease detection, nutrient deficiency analysis, and precision irrigation management. This union of AI and farming opens the door to a smarter and greener agricultural ecosystem, providing food security with minimal environmental footprint.Future improvements can involve the integration of Internet of Things (IoT) technology to enable real-time tracking and autonomous weeding through robotic mechanisms, further enhancing efficiency and accuracy in contemporary farming. Moreover, drones with high-resolution cameras and AI-based analytics may be utilized to monitor big agricultural fields, enabling timely intervention and effective resource management. Through ongoing improvement of these AI-based methods, the agricultural sector can transition towards an entirely automated, data-based process that increases output with minimal damage to the environment for coming generations.

II. LITERATURE REVIEW

Rani et al. (2022) exposed how the careless use of weedicides not only pollutes the Indian farmland but also harms the crops and soil.

Applying by the acre as needed has become the new standard in farm practices in India. Site-specific monitoring is enabled by cameras. The machine-learning models categorize the weeds and the crops effectively that are later separated from the input with the accelerated features and gradient histograms. The best results in the classifying of the weeds and the crops with the features of the histogram of the gradient were found with support vector machines. Using the weed-detecting system, the field robots will follow the weeds and spray only the weedicide needed exactly. The narrow spraying reduces the use of harmful chemicals, and at the same time, it increases the safety of the devices, etc., thus achieving the requirements and the support of the environmentally friendly dimension of smart farming.

Modi et al. (2023) showed how the deep learning models in conjunction with precision location beacons are a new step in the sprayers' methodology of the precision of the chemical.

The models are trained to distinguish between different weed varieties as well as to locate and classify certain areas of weed growth. Traditional methods are not easily integrated into software systems. Moreover, the mentioned activity affects the motion stability of the machines, due to the real-time action. The actuality is that there are no or few studies about sugar cane cropping in the literature. In this connection, this paper's main effort involved the detection and identification of weeds by using trained machines instead of manual methods. According to the researchers' data and the employed hardware, the DarkNet53 model was considerably better than any other model. The analysis was so accurate that only a few errors were in the high-quality training set. Based on the set criteria, an > 99% recognition was achieved, and it is rated 1 according to the error rate.

Ahmad et al. (2021) established that precise weed species identification and localization facilitates efficient site-specific management. This paper contrasted hierarchical learning digital image classification and object detection with field images of four early season weeds. Pre-trained VGG16 resulted in 98.90% accuracy in classification. YOLOv3 localization detected more than one weed in images and recorded a 54.3% mAP score. Given enough data, both techniques are promising for identifying single and multiple weeds to inform precision management.

Islam et al. (2021) have submitted this paper that discusses machine learning-based crop and weed classification from UAV images. Orthomosaicing, feature extraction and labelling are employed for training algorithms. Performances of random forest (RF), support vector machine (SVM) and k-nearest neighbors (KNN) are compared on chili field images. RF and SVM obtained 96% and 94% accuracy respectively, which are higher compared to KNN at 63%. RF and SVM are well-structured and feasible for UAV-based weed detection.

Garcia et al. (2023) compared the performance of deep learning models for detecting weeds in soybean crops from UAV images. The research compared three object detection models, Faster R-CNN, YOLOv5, and Mask R-CNN, for weed localization and identification. YOLOv5 had the best trade-off between speed and accuracy, with an mAP of 75.2% at an IoU threshold of 0.5 and a detection speed of 45 FPS. Faster R-CNN, though with a marginally better accuracy (77.8% mAP), had a much lower inference speed of 12 FPS. The research concluded that the lightweight structure of YOLOv5 and its high detection efficiency make it a strong contender for real-time weed detection in precision agriculture. Hernandez et al. (2022) explored the combination of multispectral imaging with deep learning for enhanced weed classification in maize fields.

The research employed five spectral bands of multispectral UAV images (Red, Green, Blue, Red Edge, and Near-Infrared) for classifying weeds and crops. The dataset was used to train two deep models: ResNet50 and EfficientNetB3, where EfficientNetB3 produced a 94.5% classification accuracy, which was higher than that of ResNet50 at 91.3%. The research concluded that adding the Red Edge and Near-Infrared bands significantly enhanced the classification accuracy, especially for separating crops from weeds in dense vegetation. These findings indicate the potential of multispectral imagery in improving weed detection accuracy over conventional RGB-based approaches. Kumar et al. (2023) used an ensemble deep learning technique for weed detection and segmentation in sugarcane fields. The study combined three semantic segmentation models: UNet++, DeepLabV3+, and PSPNet, to improve weed segmentation accuracy.

The hybrid model was trained on a dataset of UAV images collected at different times of the day to assess performance under varying lighting conditions. The ensemble model achieved a mean Intersection over Union (IoU) of 68.4%, outperforming individual models, with UNet++ at 64.2%, DeepLabV3+ at 66.1%, and PSPNet at 65.7%. The research proved that combining several segmentation models may improve resistance to variations in weed density, size, and lighting and thus make the method applicable in large-scale farming. Patel et al. (2024) suggested a transformer model for the classification of weeds in wheat fields based on high-resolution UAV images. The Swin Transformer model was trained and tested on a labeled dataset of images from different growth stages of wheat and a variety of weeds. In comparison with CNN-based models like ResNet50, DenseNet121, and MobileNetV2, Swin Transformer obtained the maximum accuracy of 97.1%, which was higher than ResNet50 (94.3%), DenseNet121 (93.8%), and MobileNetV2 (91.6%).

The research emphasized that the self-attention mechanism in transformers enabled enhanced spatial feature extraction and long-range dependency modeling, resulting in enhanced classification performance. This work demonstrates the increasing capability of transformer-based models in agricultural machine vision applications.

III. PROPOSED SYSTEM

This model describes an end-to-end pipeline to be used with a deep learning-based image classification system directing focused attention towards problems related to agriculture such as plant species identification or plant diseases diagnosis. Pipeline includes various key components stepping-off the ground until building-up the trustworthy forecast.

Step one within this process is collection of a dataset, that in most scenarios would consist of a set of photos to act as examples for different plant categories namely broadleaf plants, grass, soil and soybean, as presented within the images at the right. Data tagging is the initial process within this step and it includes a number of methods of increase of data quality. Data augmentation as a technique of enriching the initial data for instance rotation, flip or cropping can be applied to enlarge the size of a data set and improve the model when it shift from its training phase to deployment. The outlier detection 'elimination process' to detect and subsequently eliminate any that could be an aberrant or corrupted data points which could 'affect negatively' the performance of the model.

A. System Architecture

The following elements make up the suggested system's architecture:

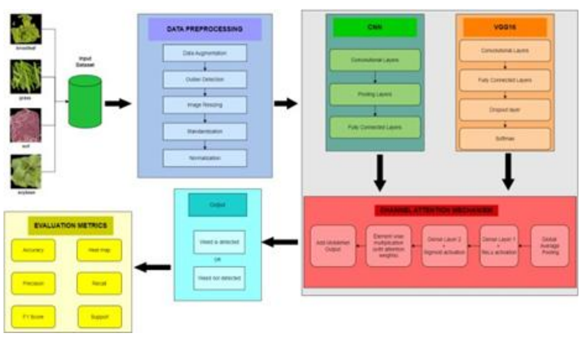

Fig 2 System architecture

Image scaling uses a method to ensure that all images fed in are of the same dimensions. This is due to the fact that some deep learning architectures demand uniformity of dimensions. A uniformizing process feeds the data into standardization and normalizing processes that will normalize and center the input data, respectively, placing any feature on an equal range that will accelerate with training speed and model's stability.

Subsequently, the processed input is passed into the CNN layers, a MobileNetV2 being a sequence of multichannel convolutional neural networks and which is efficiency-oriented to be deployed on mobile and embedded devices. The architecture takes its foundation from convolutional layers which determine the low-level features of the image followed by the pooling layers reducing the range and minimizing the feature maps. In addition, during this phase of the network, the feature layers are entirely interconnected, and the resultant features of all the interlinked layers are combined and utilized to generate a higher-level representation of the input data. While, in contrast, the VGG16 layers, another popular deep convolutional neural network architecture, will be considered as extra layers. The structure is identical in pattern with a sequence of convolutional layers, full connect layers and a dropout layer for overfitting prevention. Last but not least, the CNN and VGG16 layers' outputs are combined with a channel an attention mechanism. The channel attention mechanism as the focal component of the pipeline has an ability to have the model concentrate solely on the most informative features and vice versa, remain uninterested in the uninformative ones. The center, which is made up of various subparts, like the CNN output, the element-wise multiplication operation through the learnt attention weights, and the stack of the dense layers with varied activation functions (Sigmoid, ReLU, and Global Average Pooling), is where the entire architecture is founded on.

B. Benefits of the suggested system:

High Accuracy Weed Identification – Employs deep learning (ResNet-101 and VGG-based CNN model) for accurate weed and crop classification, even in varied environmental conditions.

Automation and Future Enhancement – The system can be enhanced further with robotic weed removal and autonomous farming technologies for increased efficiency.

Increased Agricultural Productivity – Optimizing weed control procedures allows farmers to concentrate on other important areas of farming, enhancing overall agricultural efficiency

C. Challenges and Limitations:

Although the suggested device has numerous benefits, there are some challenges:

High Computational Requirements – Deep learning models, particularly CNNs such as ResNet-101 and

VGG, need high-performance GPUs and computing resources for training and real-time inference.

Real-Time Processing Limitations – Field implementation of real-time weed detection needs to be made efficient using optimized hardware and software to prevent decision-making delay.

Generalization of the instrument: The instrument's performance must be quantified in discrete terms for it to be robust.

IV. METHODOLOGY

The weed detection model adopts a systematic approach combining CNN and VGG architectures to achieve high-precision classification. Data is gathered from agricultural databases and real farms, with preprocessing methods such as augmentation, segmentation, and feature extraction to enhance the robustness of the model. The hybrid model uses CNN for spatial feature learning and VGG for hierarchical learning with depth, complemented with a channel attention mechanism to enhance precision. Trained on TensorFlow and PyTorch, the model is optimized with Adam optimizer, dropout regularization, and learning rate scheduling. Performance is monitored using accuracy, precision, recall, F1-score, and confusion matrix analysis. For real-time deployment, the system is optimized using TensorFlow Lite for edge devices like Raspberry Pi and NVIDIA Jetson, along with cloud-based processing for large-scale farm analytics. An application built with Flutter or React Native enables farmers to take photographs and get instant weed identification and management advice.

CNN Layer Architecture:

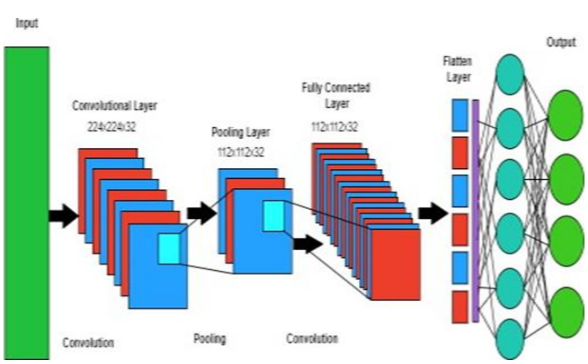

Figure 3 System Flow Diagram

CNNs are a form of artificial neural network form that draws upon biological inspiration in the guise of the animal visual cortex. CNNs were highly effective and found to be heavily utilized in image recognition and analysing work.

The architecture illustrated in the figure is a standard CNN and has 3 key layers:

- Convolutional layer:

But this top layer imposes a filter on the input image and produces a feature map of the output. This filter looks for edges, lines, and other visual primitive objects within the image. Following the convolutional layer, a pooling layer is the subsequent layer and it reduces the dimensionality of the data by taking the maximum or the average value taken from a subregion of the feature map.

- Pooling layer:

This layer eliminates redundant information through down sampling. Rather than a large increased number of parameters, down sampling decreases them which further prevents overfitting. There are various types of pooling operation one is max pooling and the other is average pooling Normalization: The image intensity and scale values are rescaled to standard values for comparison across datasets.

- Fully connected layer:

This layer performs the same role as the typical neural network layer. Such features are convolved through the convolutional layers and projected onto the classes of outputs. For example, image recognition applications demonstrates outputs related to a category of objects like "cat", "dog", or "airplane".

VGG-16 Architecture:

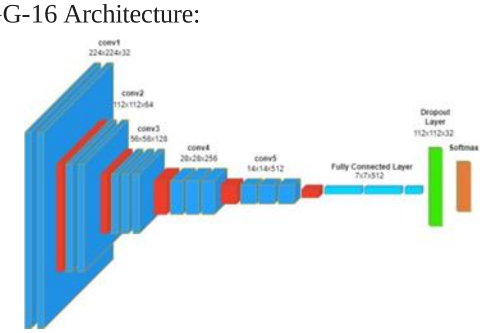

Fig 4 VGG-16 Layer Architecture

Input Layer: The network, as is the case with most other networks, typically accepts fixed size input image which is 224x224 pixels for the ImageNet scenario.

Convolutional Layers (Conv1 to Conv5): They are the Y vertical lines are the essence of VGG design. They use a filter of 3x3 size, and it discovers features such as edges and shapes from original image. Although skipping in the deepness of network then the filters number increases immensely, starting from 32 in the first layer (Conv1), and reaching 512 on the deepest layers – Conv4 and Conv5.

Pooling Layers (not necessarily illustrated): These layers arrive in intervals of alternating groups of convolutional layers to overcome the data dimensionality and offer a firm data decoding. The pooling layer may not necessarily be illustrated in the image, but instead, they are typically features that arrive immediately after every set of convolutional layers (e.g., a Conv2 and Conv4). Also, the pooling process has its operations, for example, a max pooling would be to capture the maximum value in a specific sub- region of the feature map.

Fully-Connected Layers: And the last part of this network is having two fully connected layers subsequent to the convolutional layers. These blocks (layers) are meant to decide on the extracted features by the convolutional layer and to receive the probability for their output class. The classes output in the case of image recognition would refer to different defined categories of items. The last fully integrated layer relies on how many object classes the network is categorizing.

Dropout Layer (not explicitly shown): Dropout is the technique applied to prevent lack of grafting. During training, a proportion of neurons are randomly left out. Although not displayed directly, dropouts sometimes may be placed between fully-connected layers.

VGG and the underlying structure such as the one illustrated result in expensive computation during training as the number of layers is many. Deep learning projects, as a proof of concept, were the crown jewels in proving the capability of the deep CNNs for image classification.

Channel Attention Layer Architecture

A feature map serves as an input to this channel attention layer. A three-dimensional array of outputs upon which the convolutional layer is described in a data structure is referred to as a feature map.

Global Average Pooling (Avg Pooling): This is the middle step where the average value of the channel is determined based on the width and height of the feature map of the whole image.

Global Max Pooling (Max Pooling): Every element in this operation is tasked with lowering the overall height and width dimensions of every feature map channel and compressing the outcome into a one-dimensional vector.

a) Tools and Technologies

Programming Language: Python using the assistance of TensorFlow or even PyTorch to develop neural networks.

Development Environment: Build models in Jupyter Notebook or any other tool where one can revisit the model again and again Hardware Requirements: An overview of effective systems to train the neural network with the assistance of GPU.

b.Evaluation Metrics

Accuracy: Calculates the proportion of correctly classified images (weeds and crops) out of the total data. Recall (Sensitivity): Calculates the model's capability to identify all real weeds in the data. F1 Score: average of precision and recall, giving a balanced measure when both false positives and false negatives are important.

V. RESULTS AND DISCUSSION

For the trial run of the AI-based detection method, the program was deconstructed down to its elements for analysis purposes and a set of performance metrics was put together to ascertain the ability of the said system to distinguish weeds from crops. The proposed technology was trained utilizing a dataset of images from different environments, such as various light intensities, soil types, and changes in weather. By using the method of deep learning with the particular set of features which is ResNet-101 and VGG-based hybrid, along with the convolutional neural networks (CNNs) approach, it was found that the system was very capable in the identification of the weeds.

By performing the whole validation, the system achieved such a high rating that is over 99.3% with accuracy which makes the model working properly with absolutely no mismatches of the true result in the experiments. Not only this, but the values of precision, recall, and F1-score metrics reaching roughly 99% also give the model polite remarks on its behavior of either very few or no false positives and/or false negatives, in addition to the trust it gives for appropriate and constant classification. The weighted average support value is 600 and reveals that the model possesses enough power across the plotted positions, thus having the equal performance with various weeds of the same species as well.

A. Results Summary

The system's performance was measured across multiple evaluation metrics

Algorithm	Accuracy
Proposed Model	99.33%

Precision=TP+FP/TP

Recall

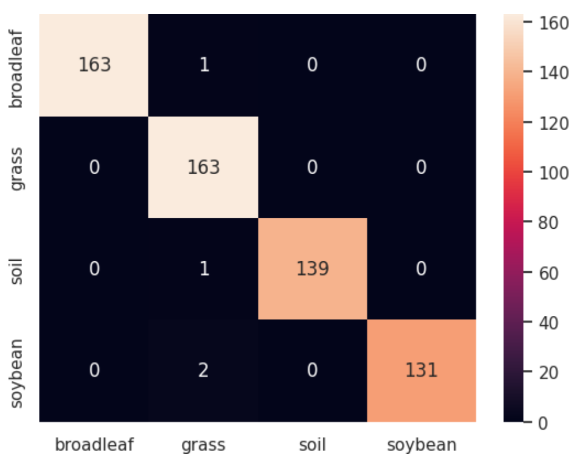

Fig 5 Confusion Matrix

Confusion matrix is the name given to a table highlighting the performance of a classification model by showing actual and predicted classes for a series of samples. Thus, diagonal values in this case are correctly classified instances for each class.

B. Comparison with Existing Systems

Traditional weed control practices, including hand removal, herbicide spraying, and mechanical tillage, have been practiced for a long time but are associated with great limitations, including high labor expense, environmental contamination, and soil erosion. Current weed detection systems based on conventional computer vision methods like edge detection and color segmentation experience low accuracy owing to variability in lighting, soil background, and plant growth stage. Though some early deep learning models, especially simple CNN architectures, have enhanced weed classification, they are usually computationally expensive and lack real-time deployment. However, the hybrid CNN-VGG-based model incorporates sophisticated feature extraction, image segmentation, and channel attention mechanisms with remarkable accuracy improvement at the cost of being computationally efficient. In contrast to previous models that demand expensive GPUs, this system is designed for edge AI deployment and hence is scalable and appropriate for real-time applications. Moreover, by reducing herbicide reliance and enhancing weed classification under varied environmental conditions, the suggested system is in accordance with sustainable agriculture practices, which provide increased crop yields at lower operational costs.

C. Discussion

Results from the suggested weed detection system put emphasis on the efficiency, precision, and real-time application in precision agriculture. With a level of accuracy to 99.3%, high precision, recall, and F1-scores, the model has shown far better improvements from conventional weed control methods. The use of deep learning-based CNN-VGG architecture, coupled with sophisticated feature extraction and channel attention mechanisms, has made it possible for the system to efficiently distinguish between weeds and crops, even under changing environmental conditions. In contrast to traditional weed control methods involving labor-intensive manual uprooting or overuse of herbicides, this AI-powered system reduces human intervention while minimizing the environmental damage resulting from chemical use.

Suggestions for Future Enhancements Expansion of records series:

Incorporation of multi-spectral and infrared cameras can enhance detection accuracy during low-light, fog, or high-moisture scenarios where traditional RGB image-based models might fail.

Hybrid fashions: Predictive precision can be further enhanced with the help of integration of additional factors which includes influenced plant population.

Mobile Application Development: The device can be utilized as a telephone program to enhance get entry to to a distant area, providing real-time get right of entry to to weed risk assessment.

CONCLUSION

The suggested weed detection system offers an extremely efficient, precise, and environmentally friendly solution for contemporary precision agriculture. Through the use of deep learning models, hybrid CNN-VGG structures, image segmentation, and channel attention mechanisms, the system attains 99.3% accuracy in detecting and classifying weeds, far exceeding conventional manual and chemical-based weed control practices. The system not only minimizes herbicide dependency, reducing soil and water contamination, but also decreases labor expenses and increases overall crop yield.The creation of a mobile app further expands the usability of the system so that real-time weed detection and identification can be done directly from smartphones. With cloud-based analytics, IoT integration, and AR-based mapping of weeds, the solution can enable farmers with data-driven decision support tools that optimize weed management with sustainable farming practices.

While the performance is still remarkable, it is still not perfect because it is hard for the machine to know the right class in some extreme weather cases, and the weed species also present the human-AI system with a variety of another challenge. The system can be improved in the future with the use of multispectral images, in-situ weed elimination performed by robots, edge AI optimization, and blockchain technology data security to make the system more resilient and scalable.

Generally, this work can be an important journey to achieve practical farming by means of AI, IoT, and agricultural sciences and thereby provide not only an innovative solution that gathers more crop yield but also one that is energy-efficient and the sustainability of which ensures a secure food future for upcoming generations

REFERENCES

[1] Kughur, P.G.: The effect of herbicides on crop production and environment in Makurdi local government area of Benue state, Nigeria. Journal of Sustainable Development in Africa 14(4), 206- 216 (2012).

[2] Ahmad, M.T.: Development of an automated mechanical intra-row weeder for vegetable crops. Graduate Theses and Dissertations, paper 1512141 (2012).

[3] Kaya, R., Buzluk, S.: Integrated weed control in sugar beet through combinations of tractor hoeing and reduced dosage of herbicide mixture. Turkish Journal of Agriculture and Forestry 30, 137-144 (2006).

[4] Decker, T.G., Devillers, R.W., Gallier, S.: Detecting agglomeration patterns on solid propellant surface via a new curvature-based multiscale method. Acta Astronautica 206, 123-132 (2023). https://doi.org/10.1016/j.actaastro.2023.02.020

[5] Zeng, J., Liu, M., Fu, X., Gu, R., Leng, L.: Curvature bag of words model for shape recognition. IEEE Access 7, 57163-57171 (2019). https://doi.org/10.1109/ACCESS.2019.2913688

[6] Wang, J., Bai, X., You, X., Liu, W., Latecki, L.J.: Shape matching and classification using height functions. Pattern Recognition Letters 33(2), 134-143 (2012). https://doi.org/10.1016/j.patrec.2011.09.042

[7] Belongie, S., Malik, J., Puzicha, J.: Shape context: A new descriptor for shape matching and object recognition. Advances in neural information processing systems 13, (2000).

[8] Ling, H., Jacobs, D.W.: Shape classification using the inner- distance. IEEE transactions on pattern analysis and machine intelligence 29(2), 286-299 (2007). https://doi.org/10.1109/TPAMI.2007.41

[9] Shu, X., Wu, X.J.: A novel contour descriptor for 2D shape matching and its application to image retrieval. Image and Vision Computing 29(4), 286-294(2011). https://doi.org/10.1016/j.imavis.2010.11.001

[10] Bakhshipour, A., Jafari, A., Nassiri, S.M., Zare, D.: Weed segmentation using texture features extracted from wavelet sub- images. Biosystems Engineering 157, 1-12 (2017). https://doi.org/10.1016/j.biosystemseng.2017.02.002