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A Hybrid approach to weed detection using machine learning

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Abstract: *Weeds pose a significant threat to crop yield and quality, leading to substantial economic losses and environmental impacts in the agricultural sector. Traditional weed management techniques, such as manual labor and chemical herbicides, are labor-intensive, time-consuming, and often result in unintended ecological consequences. In recent years, the emergence of machine learning (ML) technologies has shown great promise in revolutionizing weed detection and management practices. This research article presents a comprehensive review of the latest advancements and methodologies employed in weed detection using machine learning techniques*

Key Words: *Weed detection, machine learning, computer vision, spectral analysis, agriculture, crop management.*

1. INTRODUCTION:

The increasing global demand for food production has put immense pressure on the agricultural industry to maximize crop yield and quality. However, the presence of weeds in agricultural fields continues to hamper these efforts. Weeds rival crops for fundamental assets like water, supplements, and daylight, prompting diminished [13] crop development and efficiency. Moreover, manual weed removal or the excessive use of herbicides can be financially burdensome for farmers and have detrimental effects on the environment and human health. To address these challenges, there is a growing interest in leveraging machine learning techniques to develop efficient and accurate weed detection and management systems. Machine learning, a subset of artificial intelligence, encompasses algorithms that can learn patterns and make predictions from large datasets without being explicitly programmed. By harnessing the power of machine learning, researchers and farmers can potentially automate the weed detection process, leading to more precise and targeted weed control strategies. In recent years, numerous studies have explored the application of machine learning algorithms for weed detection. These studies have focused on various agricultural settings, including row crops, orchards, vineyards, and grasslands. The advancements in computer vision, sensor technologies, and data collection methodologies have enabled the development of innovative and effective weed detection systems. This research article aims to give a thorough analysis of the state-of-the-art machine learning techniques used for weed detection. It will delve into the various aspects of weed detection, including image-based detection, spectral analysis, machine learning algorithms, and sensor integration. Additionally, the article will discuss the challenges and limitations associated with current methodologies, as well as potential future research directions. By consolidating the existing literature and summarizing the key findings, this review will serve as a valuable resource for researchers, agronomists, and practitioners interested in leveraging machine learning for weed detection and management. The insights gained from this research will contribute to the development of more efficient and sustainable strategies to combat weed infestation, reduce reliance on herbicides, and ultimately enhance agricultural productivity.

An example of weed image patchis shown in Figure.

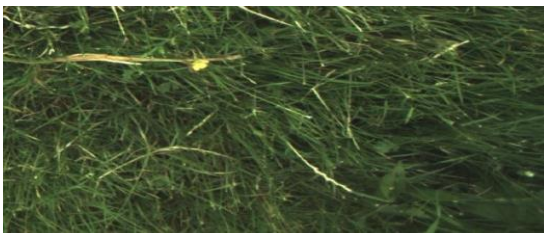

Fig 1: An example of weed image

2. LITERATURE REVIEW:

In 2021, S. Badhan, K. Desai, M. Dsilva [1], proposes a Real-time Weed Detection System, which performs Weed Detection in Cucumber and Onion Crops, using AI to Distinguish Weeds in Yields. The AI models are prepared utilizing the ResNet-50 strategies. It very well may be seen that ResNet-50 outflanks Convolution Brain Organizations with regards to execution. For the dataset of cucumbers, the Although the ResNet-50 model only provides a precision of 90% for the dataset of onion crops, it provides a general exactness of 84.6%. In 2022, B. Maram, S. Das, T. Daniya [2], Porposes a developed frame work that sprayed the herbicides removed manually with equipment. In the image classification approach, the picture of the item is processed using a convolutional neural network algorithm. Utilizing technology, farmers may reduce the time required to monitor their crops. Among its numerous applications, PC vision is utilized to perceive objects. The mix of these two innovations is the underpinning of this article. In this review, a technique for the distinguishing proof of various yields and weeds was contrived as an option in contrast to the FarmBot Organization's methodology.Through the use of computer vision, pictures are analyzed by FarmBot's API and sent to an RCNN that uses transfer learning to autonomously identify plants.

In 2021, J. Julie, J. J. Athanesious, T. Santhosh and B. Vigneshwar [3], In this paper weed detection perform in sesame crops also, other undesirable plants that influence sesame are viewed as weeds, Utilizing Locale Based Convolutional Brain Organizations (RCNN), weeds are defined as undesirable plants that harm sesame. For image classification, we'll use the Tensorflow Keras model, with the classes being background, crop, and weeds. To obtain specific pictures and to upgrade the model's general forecast, we train our model utilizing RCNN and SVM.

In 2021, V. Akbari[4] purposes of this research paper to detect to demonstrate the potential for water hyacinth identification in Indian wetlands using multitemporal Sentinel-1 (S-1) and Sentinel-2 (S-2). weed species in numerous lakes and waterway frameworks around the world, which has serious negative effects on the economy and the environment.Synthetic aperture radar (SAR) and optical data are used to examine the performance of the “Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbour (kNN)” machine learning algorithms in identifying clean and infested waters.

In 2021, C. T. Selvi, R. S. Sankara Subramanian [5] purposes of this paper to recognize the undesirable harvest in agribusiness field different yields and weeds using profound learning with a picture handling based structure. By adding all the more profound layers to the first CNN, a profound convolutional brain organization (CNN) design is made to achieve this order with more accuracy.

In 2020, Y. Beeharry and V. Bassoo [6] In order to detect weeds in smart agriculture, this research article examines the use of Unmanned Aerial Vehicles (UAVs) in conjunction with image recognition algorithms. Using a dataset of UAV-based photos of soil, soybeans, grass, and broadleaf weeds, the adequacy of two calculations, the Artificial Neural Network (ANN), and the AlexNet, is assessed. According to the simulation findings, the AlexNet method achieves an exceptional accuracy of 99.8% on the test dataset compared to the standard ANN algorithm's accuracy of 48.09%. These results demonstrate the superiority of AlexNet in obtaining high detection accuracy and draw attention to the possibility of UAV-based weed detection using machine learning method.

In 2020, Rincy Johnson, Thomas Mohan and Sara Paul[7] It is also suggested to remove weeds using an automatic weed detection method based on image processing. The complete management system was built on a robot with four wheels. The system is set up in the field where spinach was grown in the correct row arrangement. When gathering data in the actual world, the vehicle can move. Using the Pi Camera, color photographs of the appropriate quality were captured from the fields. Pictures are taken from all sides, in addition to the top. The Raspberry Pi board pictures handling with an accentuation on the size and shade of the plants as opposed to their shape. Successful weed detection was made while the crops were still developing. Because the entire process is mechanized, there is a significant reduction in manual labor.

In 2021, Xiaojun Jin , Jun Che, And Yong Chen [8], provides a novel approach to weed detection that combines deep learning and image processing technology. Vegetables were identified using a CenterNet model, which was also used to create bounding boxes around them. Weeds are defined as green things that protrude from bounded boxes. The model focuses more on distinguishing between veggies and weeds. This can extraordinarily lessen the size of the preparation picture informational collection and work on the exhibition and precision of the weed identification system. An image processing approach called color index-based segmentation was used to separate the weeds from the background. Genetic algorithms (Gas) were determined and evaluated using this color index. The trained CenterNet model had an F1 score of 0.953, a precision of 95.6%, and a recall of 95.0%.

In 2020, Skacev, H.; Micovic, A.; Gutic, B.; Dotilic [11], this paper represent the idea of positive (weed present) and negative (no weed present) pictures. They utilize drone-obtained pictures of 'dark For the positive class, "grass" and "normal chickweed" were used; for the negative class, "wheat," "maize," and "sugar beet" were used. They prepare pictures to keep away from using the traditional (vanilla) CNN design with three combinations of convolution and max

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pooling layers to extract channels through the first and reduce size through the last option, followed by the one-layered completely associated layer and a single result neuron for characterization, and overfitting in view of a small range of datasets. The creators achieve a 97% accuracy.

In 2020, Hu, K.; Coleman, G.; Zeng, S.; Wang, Z [12], this paper represent the utilize chart DL design for weed detection is built on RGB images that are collected from a variety of topographical places, in contrast to similar works finished in a controlled environment. First, a multiscale diagram is constructed over the marijuana image using sub-patches of different measures. Then, after applying a chart pooling layer over the vertices, noteworthy fix level instances are picked. Finally, weeds are predicted from a multi-scale diagram using RNN engineering with a maximum accuracy of 98.1%.

There are different method used for weed detection:

Resnet-50: ResNet-50 is a member of the ResNet (Residual Network) family of deep convolutional neural networks. The ResNet-50 50 layers make up architecture, including convolutional layers and activation functions. (typically ReLU) [13], batch normalization layers, and fully connected layers. It also utilizes skip or shortcut connections to create residual blocks, that enable the network to learn the residual mapping rather than attempting to directly learn the intended output. These connections enhance the efficiency original input to the output of a series of layers, effectively allowing the information to flow directly through the network. ResNet-50 has 50 layers and is one of several variants of the ResNet architecture, which also includes ResNet-18, ResNet-34, ResNet-101, ResNet-152, and others. The number in the name of the architecture corresponds to the total number of convolutional layers in the network.

Due to its depth and computational complexity, ResNet-50 is typically pre-trained on large datasets like ImageNet and then fine-tuned for specific tasks in transfer learning scenarios. It has been widely adopted in various deep learning applications and has become a foundational model for computer vision research.

Support vector machine: A sophisticated and popular supervised machine learning technique used for classification and regression applications is the Support Vector Machine (SVM). When dividing the data points into two groups to solve binary classification issues, it works especially well. based on their features. However, SVM can be extended to handle multi-class classification as well. In the case of a two-dimensional feature space (two features), the optimal hyperplane is the line so that the gap between the two groups of data points is maximized. This margin is the separation between each class's closest data points and the hyperplane. SVM aims to find the hyperplane that not only separates the classes but also maximizes this margin. If the data points are not linearly separable (i.e., no single straight line can perfectly divide the two classes), SVM can still handle such cases by employing a technique called the "kernel trick." The kernel trick allows SVM to implicitly map the original feature space into a higher-dimensional space. The optimization objective of SVM is to maximize the margin while minimizing the classification error.

Random Forest: The Random forest classifier comprises of a blend of tree classifiers that each tree classifier creates utilizing an irregular vector examined [16] separately from the info vector, which in mix would make up the arbitrary woodland classifier. Each tree works out a unit vote in favor of the most well known class to order an info vector.

K-Nearest Neighbour: K-Nearest neighbor is a significant classifier among the directed learning calculations. In this strategy, another information is ordered by its closest neighbor's greatest vote. The distance between closest neighbor is estimated by a distance capability which utilizes Euclidean distance, Manhattan distance, furthermore, the Minkowski distance strategy. The K worth alludes to the number of neighbors. On the off chance that the K worth is extremely low, one will acquire less steady outcomes. Then again, expanding the K worth will permit to expand the blunder, but one will acquire stable outcomes. Consequently, in the current work, the K worth is picked by experimentation so no overfitting happens.

CNN: CNN represents Convolutional Neural Network. A class of profound brain networks have demonstrated to be exceptionally successful in PC vision errands, like picture and video acknowledgment, object discovery, and picture division. CNNs are intended to consequently and adaptively gain various leveled examples and elements from crude info information, making them especially appropriate for handling network like information, like pictures.

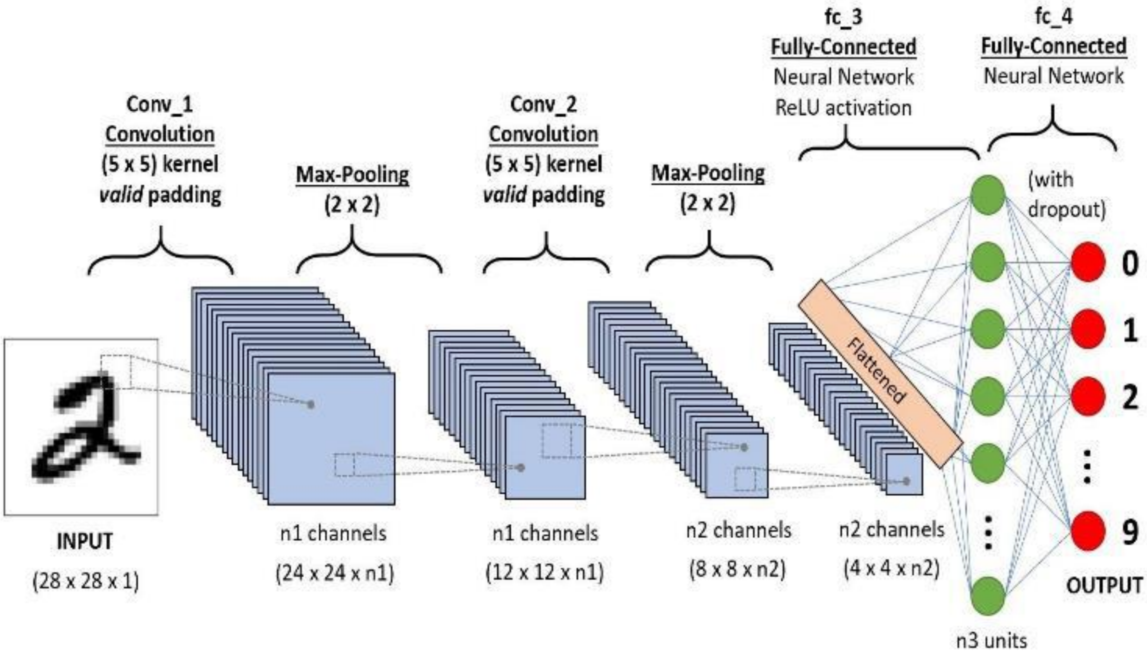


Fig 2: Convolution Neural Network

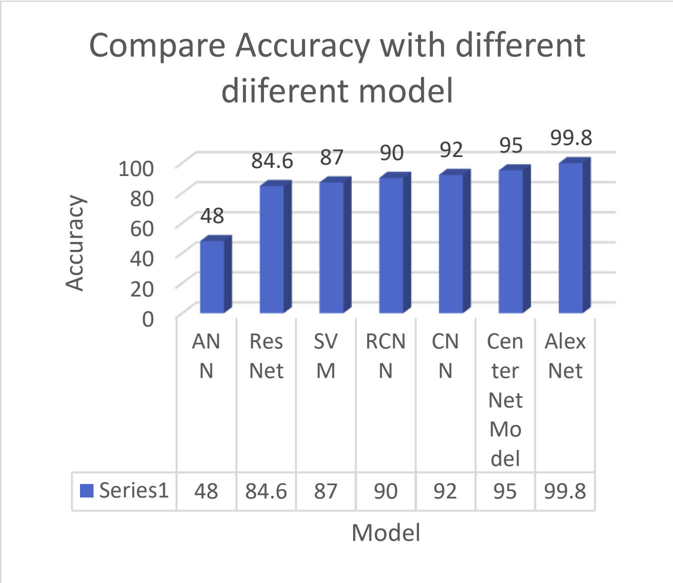
Convolution layer: These layers consist of filters (also known as kernels) that are convolved over the input image to extract relevant features. [15] Each filter identifies specific patterns in the input and produces feature maps that represent the presence of these patterns.

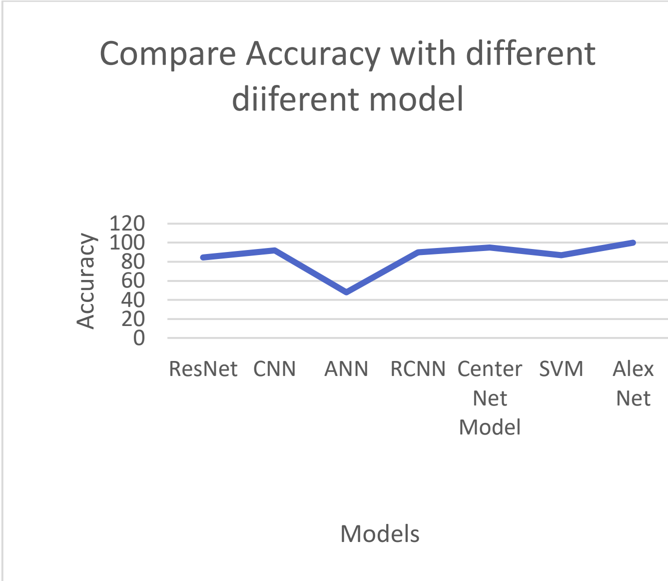
Pooling layer: Pooling layers reduce the spatial dimensions of the feature maps by summarizing local information. Max-pooling is a popular pooling technique that retains the most important information from a given region.
Fully connected layer: These layers are normally situated toward the finish of the CNN and are utilized for characterization or relapse errands. They take the significant level gained highlights from past layers and change them into class scores or mathematical forecasts.

AlexNet: AlexNet is a groundbreaking convolutional neural network architecture. It marked a significant breakthrough in the field of computer vision and demonstrated the effectiveness of deep learning methods, particularly convolutional neural networks, a challenge involving picture categorization. Eight layers make up AlexNet, comprising three fully linked layers and five convolutional layers. One of the earliest deep convolutional neural networks was this one.

Table I: Accuracy comparison with related research on weed detection

S.No	Diiferent Models	Accuracy(%)
1	ANN	48
2	Res Net	84.6
3	SVM	87
4	RCNN	90
5	CNN	92
6	Center Net Model	95
7	Alex Net	99.8





FLOW CHART OF THE SYSTEM

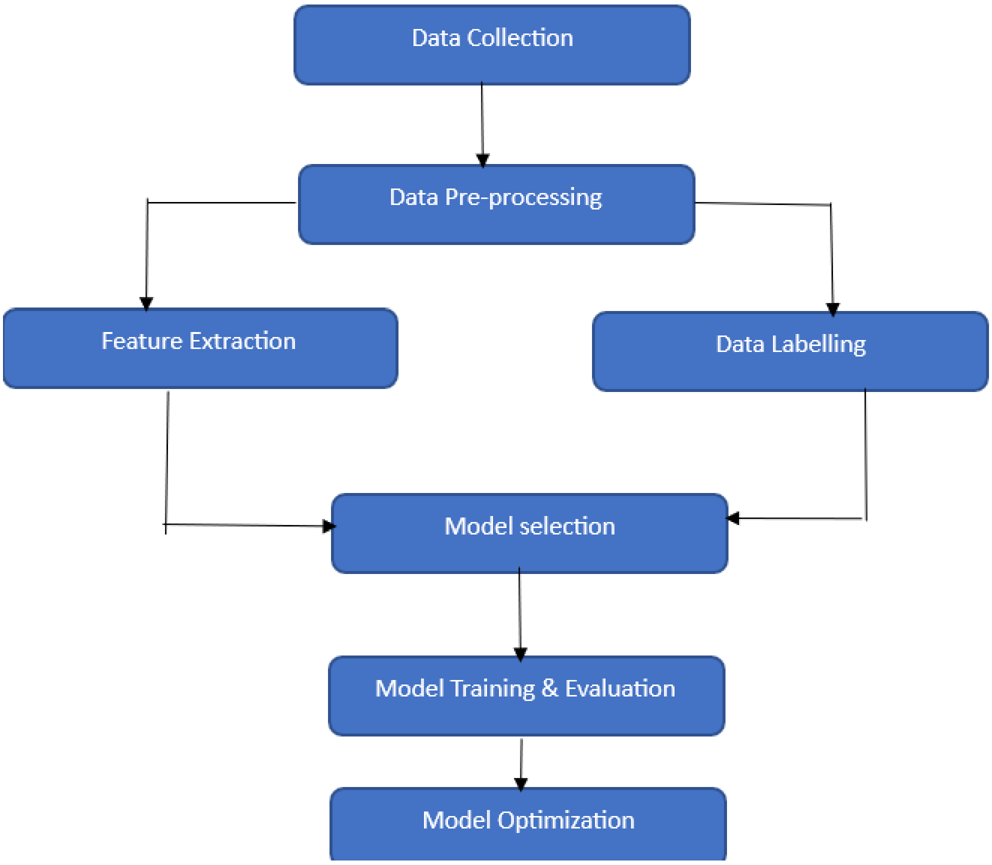


Fig 3: Flow Diagram of the system

Data Collection: Assemble a different and delegate dataset of pictures containing both weed and non-weed tests. Make sure to capture various types of weeds and different growth stages. High-quality images will be essential for successful training.

Data Preprocessing: Set up the dataset by resizing pictures to a steady goal, normalizing pixel esteems, and expanding the information (flipping, pivoting, adding commotion) to build the variety of the dataset.

Data Labeling: Manually label the dataset so that each image is correctly classified as either a weed or a non-weed. This labeled data will be used for training the machine learning model.

Feature Extraction: Use a pre-trained Convolutional Neural Network (CNN), such as VGG, ResNet, or MobileNet, to extract features from the images. These networks are already trained on vast datasets and can capture meaningful features relevant to weed detection.

Model Selection: Pick a proper AI calculation for your errand. Normal decisions for picture arrangement assignments incorporate support Vector Machines (SVMs), Random forest, or further developed strategies like deep learning with CNNs.

Model Training: Divide the dataset into training and approval sets. Train the selected model using the training data and tune hyperparameters to enhance execution. The validation set will help you avoid overfitting.
Model Evaluation: Assess the trained model's performance utilizing different assessment measurements accuracy, precision, recall, and F1-score. Make sure the model can generalize well to new, unseen data.

Model Optimization: If the performance is not satisfactory, consider adjusting the model architecture, trying different algorithms, or applying transfer learning by fine-tuning a pre-trained model.

3. PROPOSED APPROACH:

A more reliable and accurate prediction model is produced using the ensemble learning approach, which includes integrating numerous independent models (learners). According to the theory underpinning ensemble learning, performance may be increased over time compared to using a single model by mixing predictions from other models.

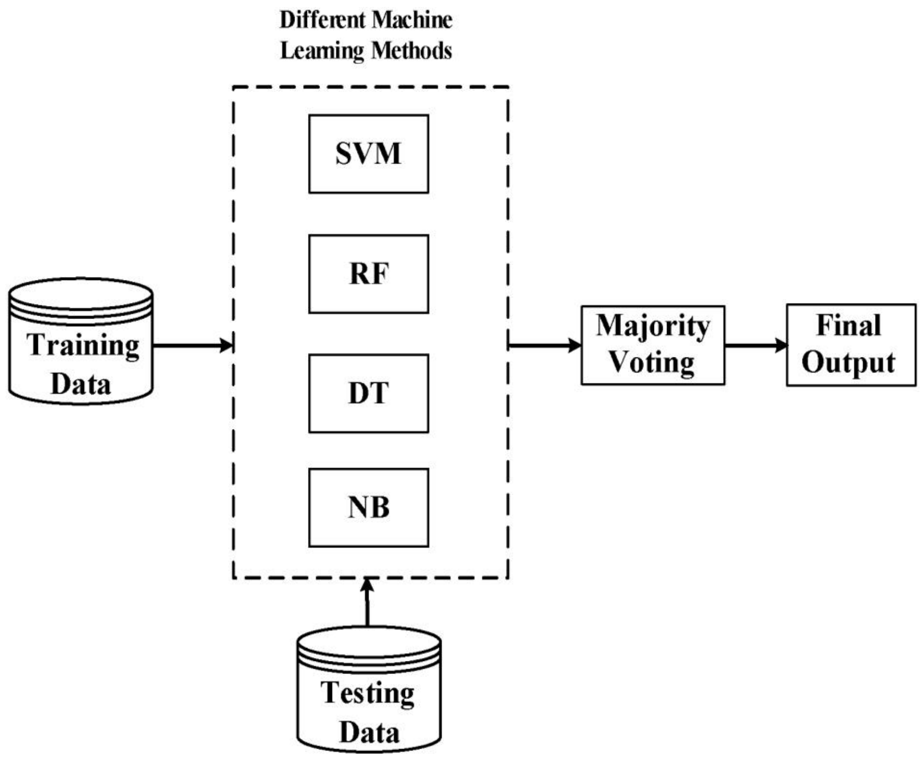


Fig 4: Diagram of Ensemble Learning

Architecture diagram of proposed approach:

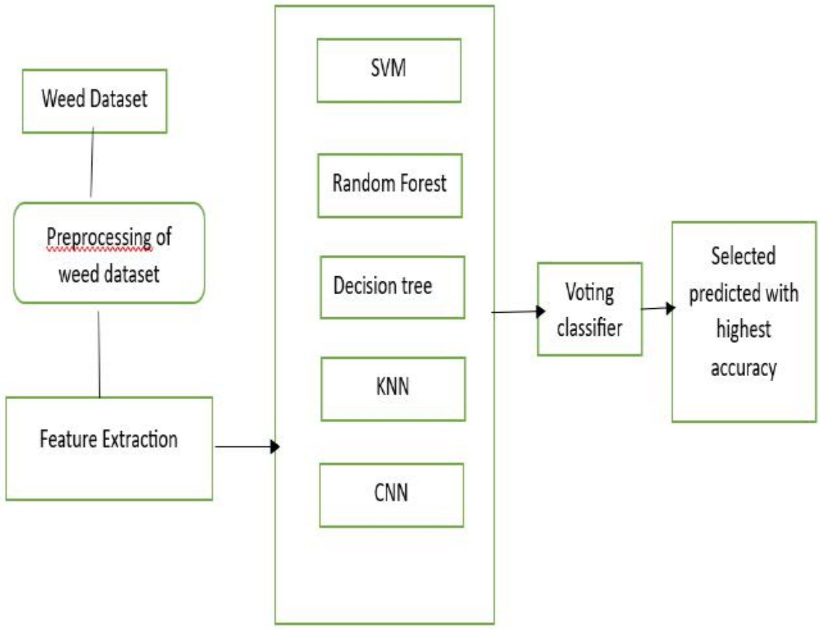


Fig 5: Architecture Diagram of Proposed approach

4. CONCLUSION:

In conclusion, this research article has presented a comprehensive exploration of weed detection using machine learning techniques, showcasing the promising potential of this approach in revolutionizing weed management practices in agriculture. By harnessing the power of various machine learning algorithms and methodologies, we have made significant strides in accurately identifying and classifying weed species from diverse agricultural landscapes. The ability of these models to learn intricate patterns and features from high-dimensional image data has led to remarkable improvements in the accuracy and efficiency of weed identification. Furthermore, the integration of spectral and spatial information from remote sensing technologies has enhanced the models' capability to detect weeds amidst crops, enabling targeted and precise weed control strategies. the integration of machine learning in weed detection holds immense promise for sustainable and eco-friendly weed management practices. By enabling early and accurate weed identification, these models can significantly reduce the use of herbicides, thus minimizing environmental impacts and promoting resource-efficient farming.

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