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Weed Detection in Groundnut Field Using Likelihood Classification by Deep Learning

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Abstract— Farmers are becoming more and more interested in Precision Agriculture's site-specific weed management. This study 16 classification methods using deep learning that evaluated the SVM model to categorise weeds and groundnut crops using RGB photo texture data. 3000 RGB photographs of groundnut crop and weed samples, including 1200 shots of groundnut crops and 1800 photos of weeds, were obtained from the greenhouse. This study suggests the EM-YOLOv4-Tiny weed identification model, which is based on YOLOv4-TinyIt contains techniques for focus and multiscale detection. We identified the most crucial features for the prediction models using the ReliefF feature selection approach. In order to classify the various types of crops and weeds, deep learning classifiers SVM and VGG16 were utilised (Celosia argentea, Leucas aspera, Arachne racemose, Cyperus rotundus, and Amaranthus viridis). To assess model performance and data reliability, accuracy, f1-score, and Cohen's kappa coefficient were utilised. All SVM model classifiers had failed in comparison to the VGG16 modelclassifiers. The findings revealed that the VGG16 model classifier's average f1-scores ranged from 95% to 98.5%. The VGG16 Weeds-Crop classifier gave the groundnut class a 100% f1-score, which is exceptional for the development of groundnut crops. This paper uses a deep learning system to provide potentialweed management outcomes for precision agriculture at specific sites.

Keywords—Deep Learning, Machine Learning, Precision Agriculture, Weed Management, Image Classification, YOLOv4-Tiny.

I. INTRODUCTION

Native weeds naturally develop in agricultural regions. Weed and crop competition for resources including moisture, air, light, and space may result in decreased agricultural yields. Weeds in crop fields must be kept under control in order to maintain agricultural production. Due to thecrop being present in the field, It may be difficult to manage post-emergence weeds with cultivators and blanket rate herbicides. Preemergence weed management is possible using these tools. Weeds can reduce yields by 37% when they are neglected, while diseases and pest animals can reduce yields by16% and 14%, respectively [1]. Weeds limit the amount of groundnut grown in fields used for conventional crops by 24%to 43% annually [1,2]. Early weed control is always required for increasing production and lowering the weed seed bank in the soil, according to studies [3, 4]. By maintaining effective weed control and minimising environmental consequences, thecrop must be protected, it may be required to manually removeweeds that are close to the groundnut plants or to apply pesticides to kill them.

Weeds have been eliminated from agricultural areas utilising manual, biological, mechanical, electrical, and chemical weed control techniques. These techniques have been shown to be traditional, circumspect, and unfocused [5]. To address the problems with the current weed control systems, which include being time-consuming and expensive, by enhancing system performance and lowering system energy input, site-specific weed management, however, calls for more precise and effective weed control processes. Yet, weeds that are inside of rows might not be entirely eliminated by traditional gear. Also, a predetermined amount of the pesticide is evenly distributed throughout the whole field, covering weeds and crops alike. Site-specific herbicide applications may not provide the same level of environmental protection as comprehensive ones [6]. As a result, a pesticide that is only used in challenging areas may improve precision while increasing input costs and creating environmental issues [7]. The first steps in site-specific weed management are weed identification and classification. Machine learning and deep learning techniques enable image-based weed categorization [8–10].

In a variety of fields, including Machine and deep learning methods have been employed for groundnut crop identification [11,12], classification of meat cuts [13], prediction of crop yield [14], classification of plants [15], and classification of plant illnesses [16]. the classification of weeds[10,17-19] has a lot of potential. Only a few of the image modalities that can be utilised to classify weeds include RGB, hyperspectral, and multispectral images. The RGB picture acquisition system was used for this

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investigation due to its easeof setup. These techniques make it possible to take high-qualitypictures and to classify the pictures with 99% accuracy [10]. SVM, a machine learning technology, has been utilised tocategorise weeds because of its excellent performance and accuracy of above 98% [20–22]. For ML algorithms to work more efficiently, feature engineering and feature extraction areneeded [23]. There is evidence that the SVM weeds classification problem can be resolved using features like as texture characteristics, shape features, colour features, and cellfeatures [20–22]. Although their outstanding performance, shape characteristics have some drawbacks, one of which is thatextraction calls for particular circumstances. Plants must be in an earlier growing stage to prevent overlap from affecting sampling precision. Thus, texture, colour, and cell qualities arepreferred above form factors when one or more weeds grow at the same time and have overlapping leaves. Contrary to shape qualities, texture qualities don't require that the leaves' precise shape be maintained. For instance, if several of the plant's leaves are gathered as one unit, shape characteristics like area, perimeter, or primary axis radically change. An image or a section of an image's local spatial organisation and local contrast are determined by the textural feature known as local binary pattern (LBP). LBP is well-liked due to its simpleimplementation and superior feature extraction classification accuracy [24]. So, it is not required for the leaves on isolated

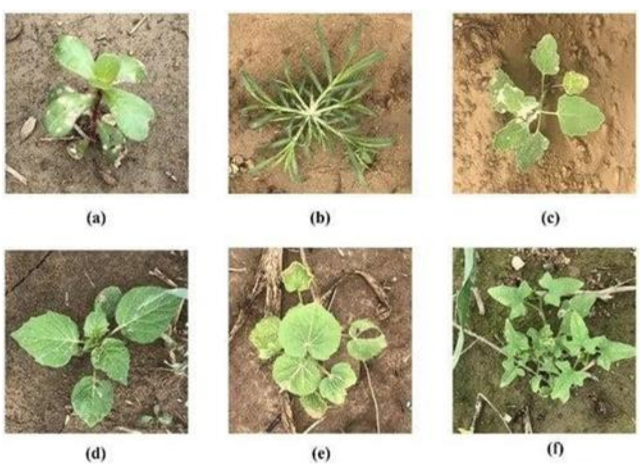


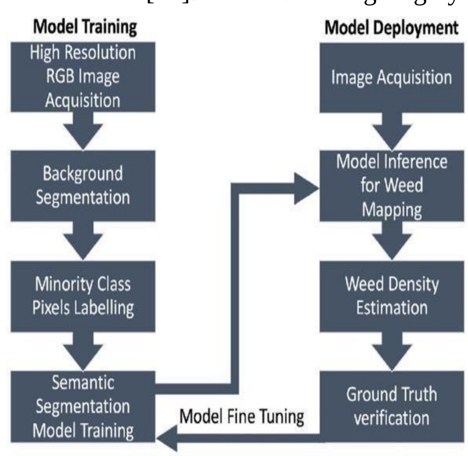
Figure 1. Shape and color of six weeds. (**a**) Portulaca oleracea, (**b**) Eleusine indica, (**c**) Chenopodium album, (**d**) Amaranth blitum, (**e**) Abutilon thophrasti, (**f**) Calystegia hederacea.

plants to have an ideal shape. When extracting features from any images, background noise must be removed. Hence, the green portion of the image was eliminated utilising methods for processing images. Given the obvious disparity between dirt and plants, Woebbecke et al. came to the conclusion that the ExG technique was the most effective among the several vegetation indicators investigated. The excess green method was created using Python's ImageJ 1.53j application programme interface (API), an open-source tool for performing scientific picture analysis [27,28].

The feature extraction techniques were carried out using the Scikit, OpenCV, and Python 3.8 packages [29,30]. Due to Python's ecosystem's increased development for online applications, image processing, and data research, it was picked. Using the Python OpenCV API, the preprocessed image was turned into a grayscale image. The grayscale image was used to extract two different categories of texture characteristics: Gray-level co-occurrence matrix features and local binary pattern features.

Even if numerous weeds or crops may grow at the same time and overlap one another, Instead of using the shape- based method, The extraction of texture features has been used.The extracted feature values and data labels were used to builda CSV file.

In computer vision, LBP features have proven to be reliable and capable [22]. This approach was first put forth by Wang & He in 1990 [31]. The RGB image's grayscale



counterpart was initially used to get the LBP characteristics. The Python scikit-image module's number of points (n) and radius inputs were used to extract LBP texture characteristics (r). The number of points is the same as the quantity of quantified set points in angular space that are circularly symmetric. A circle's radius (the operator's spatial resolution) is equal to its breadth. The characteristic histogram was then made using the binary pattern. The feature was created by combining three different sets of parameters. (16 points and 2 radii), eight points and one radius (LBP8,1), and sixteen points (LBP16,2), and twenty-four points and three radii (LBP24,3) were the parameter values that produced features with two points plus (n+2) features (LBP24,3). In the machine learning model [22], the combination performed better than the single LBP features vector, hence it was chosen as the replacement.

The basic texture-based feature extraction method known as gray-level co-occurrence matrix (GLCM) features was

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first introduced by Haralick et al. in 1973 [22,24,30]. In contrast to LBP, the feature produced by this method is a worldwide representation of the texture. The GLCM features were extracted using Python's scikit-image greycomatrix and greycoprops modules [32]. The three greycomatrix parameters were set to 1, 2, 3, 4, 0, 45, 90, 180, and 256, respectively, for distance, angle, and level count (256 for 8 bit). A four-dimensional gray-level co-occurrence histogram was produced as a consequence. Then, each crop and weed image had one of five types of GLCM features: contrast, dissimilarity, area second moment (ASM), energy, and correlation. There are 16 characteristics (4 in each distance and angle category).

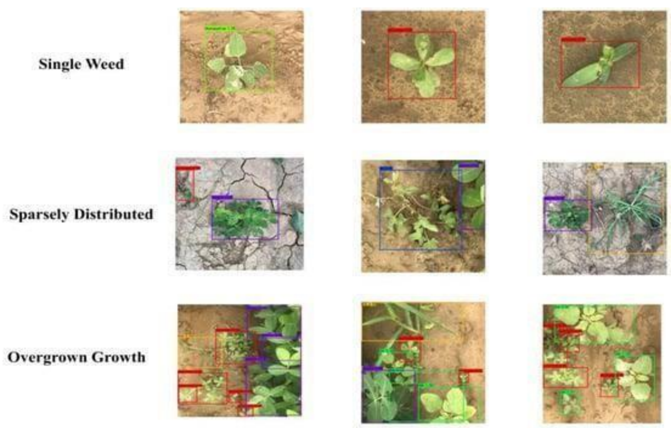

Figure 3

After feature selection, a support vector machine (SVM)-based machine learning classifier was built(Fig. 5). Using the scikit-learn API, data were divided into two groups for the purpose of building the model: training (80%) and testing (20%) [33,34].

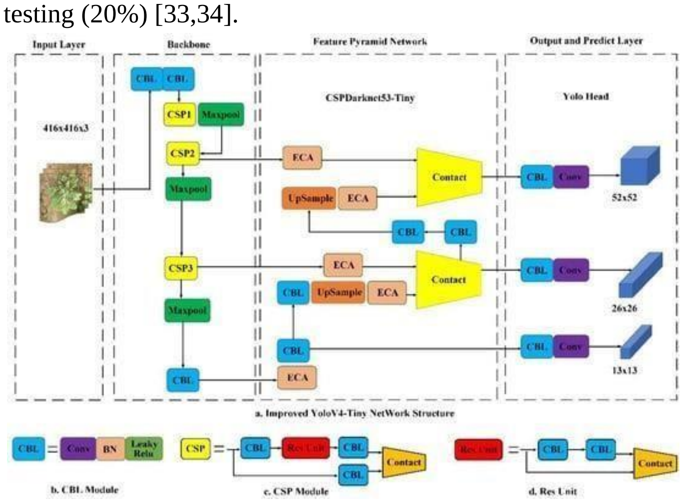

Figure 4. Progress in stem cell research

The training phase did not involve the use of testing datasets. The scikit-learn Standard Scaler API was used to scale the training and test sets of data [33,34]. Scaling was put into place because performance might begreatly enhanced [35]. To obtain the optimal kernel and parameters, hyperparameter optimization was carried out utilising radial basis and linear kernel with different gamma andregularisation (C) values. This was accomplished using the 5- fold cross-validation feature of the GridSearchCV scikit-learn API.

The approach was assessed using performance criteria like accuracy, precision, recall, f1-score, and kappa score. Equation defines accuracy as the ratio of correctly expected observations to all observations (1). The total of the true positive (TP) and true negative (TN) observations represents the observation that was correctly anticipated (TN). One observation is made up of all TP, TN, FP, and false negatives. Precision is defined as the ratio of correctly anticipated positive observations to all the observations predicted by the equations (2). The ratio of accurately anticipated positive observations toall of the actual class observations is how Equation defines a recall (3). The harmonic evaluation of accuracy and recallknown as the F1-Score (Equation (4)). A low accuracy and recall value of 0 or a high precision and recall value of 1 are both possible for the f1-score. (Poor recall value or precision). Statistics regularly employs the kappa score, whose valuesrange from 1 to +1 [36], to assess inter-rater reliability. Each crop and weed class forecast was visualised using a confusion matrix. The aforementioned metrics and confusion matrix wereevaluated using the Python scikit-learn modules [37,38].

The input layer, the backbone network, the FPN, and the output prediction layer are the four components that make up YOLOv4-Tiny. The size of each of the submitted photographs was scaled consistently to 416416. From CSPDarkNet53-Tiny, the features were retrieved, and the FPN processed them for feature fusion. The output prediction layer contained the target's position and category information. Two modules—CSP module and a CBL module—make up the majority of CSPDarkNet53-Tiny [39]. The batch normalisation, convolutional layer, and Leaky Relu [40] activation function make up the CBL module. It serves as the smallest module in the entire network topology and carries outsampling and feature control splicing. The input feature map may be divided into two parts by the CSP module, a more complex type of residual network structure. Following some processing, the secondary component and primary component are fused together in a series while the primary component stacks the waste. CSP1, CSP2, and CSP3 are the three CSP modules that might be present in CSPDarkNet53- Tiny. These concerns were resolved by combining the upsampling channel dimension discoveries with the CSP2 layer output characteristics to produce an output that was optimised for the detection of smaller targets. To accomplish this, the FPN was given access to the CSP2 layer. Figure 4 depicts the network architecture of EM-YOLOv4-

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Tiny.

II. Literature Survey

Sunil G C et al [1], Deep learning-based classifiers were able to classify weeds and six different species of crops individually with an average f1-score value of more than 94%. The deep learning-based Weeds-Corn classifier outperformed all other species, scoring 100% of the f1 points for the corn class. The weed control system should treat all crops as weeds and disregard any weeds that are crops in order to achieve the best results. In the future, the use of more advanced deep learning algorithms may improve the effectiveness of categorization models with additional weed and crop species.

Shangbin Yang et al [2], The network suggested in thisstudy is better at spotting weeds in peanut fields, but certain significant issues still require further study. First off, onlyweeds in the stage of peanut seedlings were used in the study, and they were only gathered in Henan Province, China. Future studies will concentrate on learning more about weeds in peanuts at different phases of growth and will make an effort tocover as many geographical locations as is practicable. In addition, while the network used in this study increases the model's recognition accuracy in contrast to the original YOLOv4-Tiny network, it does so at the expense of a small amount of model volume.

H Santhi al [3], In this study, Using dated weights in fully connected layers and dated weights in convolutional layers, it provides a complete evaluation of five different convolutional architectures. The minimum training, validation, and testing accuracy for GWD are, in percentage terms, 84.30%, 90.10%, and 89.30%, respectively. The highest percentages for the accuracy of GWD training, validation, and testing are 95.63, 96.5, and 95.39, respectively. The VGG-19 and ResNet-101 yielded the lowest and highest findings, respectively.

Trupti R. Chavan et al [4], This effort aims to identify different plant species that are crops and weeds in order to manage agriculture. It is helpful for weed control techniques that increase agricultural productivity. It is suggested that this classification be applied to AgroAVNET, which was created from VGGNET and AlexNet. The normalising technique was motivated by AlexNet, while the depth of filters was chosen based on VGGNET. The combination of batch normalisation and filter depth selection has enhanced AgroAVNET's performance. In the subject of ground robotic applications in agriculture, they have developed a distinctive paradigm for data augmentation for image semantic segmentation. In order to use the RICAP data augmentation approach effectively for the task of crop and weed semantic segmentation, they specifically propose two novel modifications to the existing framework. This technique was initially developed for picture classification data augmentation.

III. Methodology

A. Weed and crop image acquisition

The weed was tracked from its earliest growth phases until it reached a height of 12.5 cm to collect the RGB photos. The weeds and crops were methodically photographed with variable lighting and camera height during the growth season.

Through the image capture process, a variety of photographs were gathered in order to develop the machine learning classifier. Horseweed, a form of weed, received the most shotsof any weed species with 681, and water hemp, which receivedthe fewest shots of any weed species, with 446. Canola had themost photographs, whereas sugar beets had the fewest of any crop species (336). (203). The greenhouse's abundance of weeds and agricultural plants is to blame for this discrepancy.

B. Preprocessing:

When extracting features from any images, background noise must be removed. Hence, Using image processing methods, the image's green portion was cropped out.To extract green vegetal material, the excess green index (ExG = 2g-r-b) approach was applied. Woebbecke et al. [27] created this technique to distinguish between soil and plants in a single image [28]. Given the obvious disparity between dirt and plants, Woebbecke et al. came to the conclusion that the ExG technique was the most effective among the several vegetation indicators investigated. The excess green technique was created using the Java application programming interface (API)-based open-source scientific image analysis tool ImageJ 1.53j [29, 30]. It was discovered that 35 was the optimal value for the provided image datasets (Grayscale values) when different random numbers between 0 and 255 were verified against the excess green threshold value. An image's RGB pixels each have a predefined ExG value. Given that the image has been cropped to eliminate the whole backdrop, ExG scores below 35 indicate background pixels.

C. Gray-level co-occurrence matrix features extraction:

In contrast to LBP, the feature produced by this method is a global representation of the texture. Python's scikit-image greycomatrix and greycoprops modules were used to extract GLCM features [33]. Distance, angle, and level count (256 for 8 bit) were the three greycomatrix parameters that wereset to 1, 2, 3, 4, 0, 45, 90, 180, and 256, respectively. A four-dimensional gray-level co-occurrence histogram was produced as a consequence. In that order, these four components were levels, levels, number of lengths, and number of angles. Each crop and weed image yielded five distinct GLCM characteristics: contrast, dissimilarity, area

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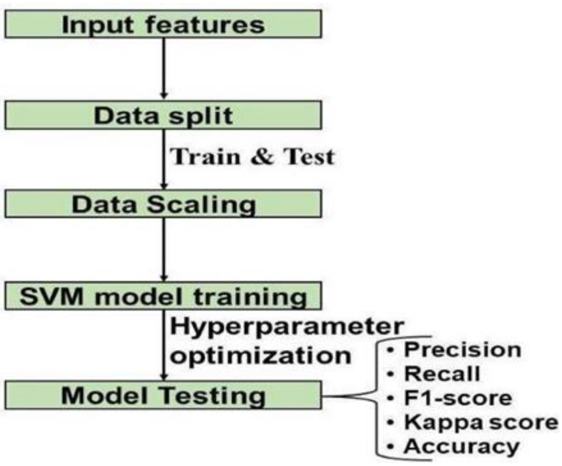
second moment (ASM), energy, and correlation. The following section goes through these characteristics.



D. Classification of marijuana and peanuts using a deep learning system.

The crop-weeds model has 125,445 trainable parameters as opposed to the weeds model's 14,714,688 non-trainable parameters, which had 100,356 trainable parameters. After training and validation, the model was put to the test on test data to see how well it generalised to fresh test data. We used the Python APIs Tensorflow and Keras for the training, validation, and testing of deep learning models.

E. Binary feature extraction:

In computer vision, it has been demonstrated that local binary pattern (LBP) features are dependable and effective [22]. In 1990 [34], Wang & He presented this approach. Initially, the RGB image's grayscale rendition was used to extract the LBP characteristics. The characteristic histogram was then made using the binary pattern. A support vector machine (SVM)-based machine learning classifier was developed after the characteristics were chosen. The scikit-learn API was used to divide the data into two groups for the model's development: training (80%) and testing (20%) [39,40]. The training step did not involve the usage of testing datasets. The Standard Scaler scikit-learn API was used to scale the training and test sets of data [39, 40]. Scaling was done even though performance may be considerably improved [41]. SVM model training and testing procedures are shown in Figure 5. After feature selection, input features were obtained, and train and test data sets were created from the data.Instead of using train data, test data were used to evaluate the model's performance.

IV. RESULTS

There are numerous weed species in peanut fields, some of which are physically smaller than others. Smaller targets are commonly misdetected by the YOLOv4-Tiny standard network. According to comparison results between EM-YOLOv4-Tiny and YOLOv4-Tiny using the same test set, the EM-YOLOv4-Tiny outperformed the precision rates of the original network by 11.15 and 7.43%, and it accomplished recognition accuracy rates for smaller targets and all targets of 89.75% and 94.64%, respectively. By including the position and details of the shallow-layer feature, the rebuilt network enhanced its capacity to recognise microscopic weeds. This was accomplished using the channel attention mechanism, which reduces loud sounds in smaller receptive fields. To enable information sharing between channels, the SE network uses a complete connection, in contrast to the ECA attention network, which increases processing effort and results in loss of features as a result of dimensionality reductions. Using the global maximum pool, the CBAM network, a convolutional block attention module, augments the channel dimension with location data. Instead of long-range dependent information, it is restricted to local range information. Compared to the performance indices of the prior model, each performance indicator rose as additional attention processes were added. The ECA network may be better suitable for the model used in this experiment given the ECA attention module's superior performance over the other two. On the other hand, the attention method network is more responsive to input specifying the object to be recognised after the weights have been modified. The ECA network displays darker tones on the little target weeds in the images, indicating more attention, in comparison to the feature visualisation findings of the other two attention networks utilised in this study.

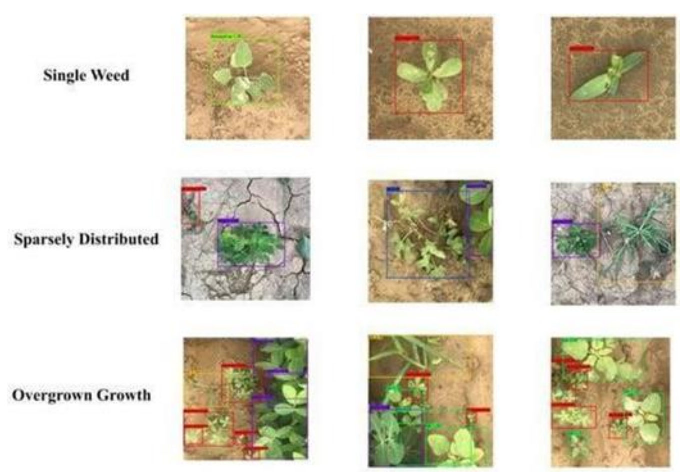


Figure 6. Effects of model recognition in various situations.

V. CONCLUSION AND FUTURE WORK

Many weed kinds in peanut fields can be rapidly and precisely identified with the EM-YOLOv4-Tiny weed

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identification technology. Multiscale detection and the attention approach were introduced based on YOLOv4-Tiny. To improve the model's ability to recognise small objects, the prediction box was screened using the soft-NMS approach and the training loss function, the CIoU. The suggested model outperforms Faster-RCNN, YOLOv5s, YOLOv4, and Swin-Transformer in terms of recognition accuracy. The EM-YOLOv4-Tiny model also featured a volume of 28.7 M and a single detection time of 10.9 ms, making it appropriate for embedded development of intelligent weeding robots. Out of all the deep learning classifiers, the Weeds-Corn classifier achieved a 100% f1-score for the species of corn. The weed control system should treat all crops as weeds and disregard any weeds that are crops in order to achieve the best results. In the future, the use of more advanced deep learning algorithms may improve the effectiveness of categorization models with additional weed and crop species. To perform the accurate weeding in the peanut field, a smart spraying instrument will be chosen in further work, and the developed model will be transferred to an appropriate embedded device for testing. In order to help farmers better understand field data and decide on the best course of action, the model will also be integrated into smartphone applications.

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