Hybrid features and ensembles of convolution neural networks for weed detection

Sandeep Kumar Kempegowda, Rajeswari, Lakshmikanth Satyanarayana, Siddesh Matada Basavarajaiah
Department of Electronics and Communication Engineering, Acharya Institute of Technology, Bengaluru, India

Article Info

Article history:

Received Sep 7, 2021
Revised Jun 21, 2022
Accepted Jul 18, 2022

Keywords:

Bayesian optimization
Color moments
Convolution neural network
Gabor wavelet
Grey level co-occurrence
Support vector machine

ABSTRACT

Weeds compete with plants for sunlight, nutrients and water. Conventional weed management involves spraying of herbicides to the entire crop which increases the cost of cultivation, decreasing the quality of the crop, in turn affecting human health. Precise automatic spraying of the herbicides on weeds has been in research and use. This paper discusses automatic weed detection using hybrid features which is generated by extracting the deep features from convolutional neural network (CNN) along with the texture and color features. The color and texture features are extracted by color moments, gray level co-occurrence matrix (GLCM) and Gabor wavelet transform. The proposed hybrid features are classified by Bayesian optimized support vector machine (BO-SVM) classifier. The experimental results read that the proposed hybrid features yield a maximum accuracy of 95.83%, higher precision, sensitivity and F-score. A performance analysis of the proposed hybrid features with BO-SVM classifier in terms of the evaluation parameters is made using the images from crop weed field image dataset.

Corresponding Author:

Sandeep Kumar Kempegowda
Department of Electronics and Communication Engineering, Acharya Institute of Technology
Acharya Doctor Sarvepalli Radhakrishnan Rd, Soladevanahalli, Bengaluru, Karnataka, India
Email: sandy85gowda@gmail.com

1. INTRODUCTION

Agriculture is currently facing immense challenges, given the need to increase food production and growing concerns about environmental issues and climate change. Crop yields have skyrocketed over the past 30 years, thanks to better crop management and improved irrigation and fertilization systems [1]. Meeting future food demand will largely depend on sustainable crop growth. However, at the moment, the rate of increase in potential profits is much lower than expected due to increased demand [2].

One of the proposed approaches to solving this problem is sustainable agricultural growth, which aims to increase food production in the existing country, minimize environmental impact, and meet the needs of present generations and future goals [3]. To achieve sustainable production at this high level without harming the environment, it is essential to improve the eminence of the soil and to properly control all factors of production in time and space. Hence, this progress is clearly needed to integrate important approaches to agricultural research and development. In the technical aspect of large-scale sustainable agriculture, precision farming (PF) plays an important role and introduces an ideology that sees the field as a diverse object with variability in many dimensions [2]. It has been argued that various types of information technology and communication systems are major contributors to the resilience transformation, and agricultural support systems are an important part of the resilience transition. PF is an agricultural management idea based on observing, measuring and acting on local and temporal cultivation diversity. The goal of PF is to express a decision support system for crop management in order to maximize input yields and conserve resources [4], [5]. Precision farming involves more efficient management of production inputs and agricultural inputs such as herbicides, pesticides, water, and fertilizers, with the correct crop management in the correct place and at the correct time. Although most of the large agricultural areas that are traditionally managed have these inputs coordinated, the PF can divide the area into different management areas as resources are allocated according to the characteristics of each region. PF seeks to improve crop yield and profitability through better management of agricultural resources, which it relies on to accumulate cultural data and information over time and space [6].

Weed detection using computer vision techniques has shown promising avenues in precision farming. Computer vision uses special image processing techniques for segmentation and classification for weed detection. Weeds in agricultural fields can be distinguished by its possessions such as spectral reflectance, shape, dimension, and texture features, based on the positions of weeds, herbicide sprayers are controlled to spray right on desired areas of the weed in the field. However, the automation in terms of the precision in weed detection using computer vision techniques still poses an open problem for research in the area. Weed detection with machine learning is revolutionary and allows us to dramatically reduce manual work and research costs.

This paper is structured as follows. Section 2 gives the overview of the related works carried out in weed detection. Section 3 shows the proposed hybrid weed detection methodology. Simulation and results are presented in section 4 followed by conclusion and future perspective in section 5.

2. RELATED WORK

Image processing is getting more popular in weed detection process; Its specific processes include certain preprocessing, image segmentation to find the region of interest, feature extraction to define the certain pattern, and classification using machine learning for detection and classification [7]. Bakhshipour *et al.* [8] represents wavelet texture-based features are used to distinguish between weed and crops in sugar beet crops. Wavelet texture is trained with artificial neural network for weed identification. Montalvo *et al.* [9] Used image segmentation for the detection of rows of cultures, by using double threshold 3D-Otsu method. Further weed and crop identification was achieved by using the principal component analysis (PCA) method. Bakhshipour and Jafari [10] proposed size parameters by geometry of weed and further support vector machine (SVM) used for classification of different type of weeds.

The studies [11]–[13] used an SVM and a traditional neural network classifier with scale-invariant feature transform (SIFT) feature extractor. Alam *et al.* [14] used the grey level co-occurrence matrix (GLCM) with the Haralick descriptor as the texture characteristic and the *ndi* as the color for the classification. The results showed 99% accuracy in detecting weeds in the test data, limiting weeds and rice plants of the same size. However, the main limiting factor for the weed detection system described above is the manually extracted elements (color information, and other color conversions may require corresponding values, shape analysis i.e., various geometric and morphological structures and texture analysis for accurate visualization as well as various image classification problems such as changing perspective, scale and gradation, image distortion, image overlap, lighting, and background clutter.

In recent years, researchers have developed systems that include deep learning techniques for identifying weeds or other crops. The most common deep learning tool for weed detection is the convolutional neural network (CNN) [15]. This type of neural network is complex but effective, has a high recognition rate and has shown good results in precision farming for correct plant identification. Compared to the previous method, CNN is less susceptible to natural changes due to self-learning properties such as changing lighting, leaf asymmetry, and plant spread. Today, CNNs are being used in complex crop and weed detection systems to push the boundaries of artistic approaches and achieve the highest productivity. Di Cicco *et al.* [16] utilized the CNN cascade to identify tumors/weeds, with CNN classifying vegetation first and then classifying vegetation pixels using CNN deep-growing grasses. McCool *et al.* [17] maintained very complete compliance with CNN and achieved practical processing time by compressing the optimized network using a combination of smaller but faster networks without much loss of recognition accuracy. Full CNN directly estimates the overall pixel segmentation of an image and can use general information about the image. Finally, Milioto *et al*. [18] proposed an encoded CNN decoder that uses existing vegetation metrics and performs real-time detection. Beeharry and Bassoo [19] used a torsion neural network (CNN-AlexNet) to identify weeds in harvested soybeans, classify weeds between grasses and deciduous crops, and apply special herbicides to identify weeds. This work shows an accuracy of 97%. Experimental results showed that the characteristics of self-controlled plants/weeds were close to those of the model with manually labeled training data [20]. An SVM alignment that combines surface color and edge shape improves overall alignment accuracy to 99.07%. Dyrmann *et al.* [21] proposed a method for automating weeds in color images in case of significant leaf blockage. The algorithm was able to detect 46% of the weeds when the majority of the weeds overlapped the wheat crop. When the weeds are exposed to a large overlap, the proposed algorithm decreases productivity. Studies of [20], [22] show that the ability to use aerial photographs for weed control is highly dependent on the type of camera, flight altitude and temporal resolution. Advanced neural networks can be used to extract resources, and the extracted resources are used in cases such as sorting, extracting or recognizing, sorting, extracting or recognizing. Convolutional neural networks can be used to extract resources, and the extracted resources are used in cases such as sorting, extracting or recognizing, sorting, extracting, or recognizing. Some of the limitations of deep learning require training a large number of sample images as a tailored solution to distinguish between crops and weeds.

3. RESEARCH METHOD

This paper presents the weed detection from carrot plant leaves using deep, texture and color features-based feature extraction followed by convolutional neural network-based hybrid features classification with the Bayesian optimized SVM. The generalized block diagram of proposed approach is shown in Figure 1. In the proposed novel weed detection mechanism, it uses a hybrid of convolutional neural networks and a combination of descriptors to generate a novel image descriptor. Initially the input image is taken from the dataset and then resized to 227×227×3. The second step is feature extraction where a deep feature extractor (an enhanced CNN AlexNet) and handcrafted descriptors such as color moment, Gabor wavelet, and GLCM features make up the segmented image. On the other hand, the advanced AlexNet CNN processes the image and identifies its pattern, and finally gives a vector of characteristics with dimensions of 1×64. An additional fusion of deep features and handcrafted hybrid features is implemented in Bayesian optimized SVM models for classification. The findings of this research work quantify the comparative importance of each of the above variables in performance enhancement and validated using simulation results. The upcoming headings describe the materials and methods used throughout the different stages of experimentation and data processing. Following are the details for each block.

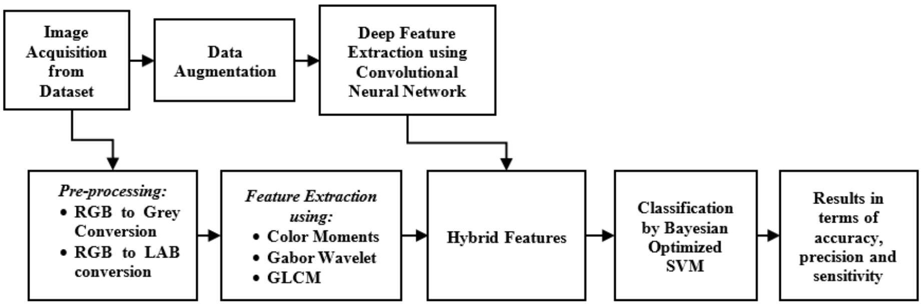

Figure 1 Block diagram for hybrid approach of weed detection

3.1. Image acquisition from dataset

The dataset represents the agricultural field of study in which the images were taken. The dataset contains 60 captured images and is accessible online [23] as shown in Figure 2. All images were taken with the help of independent acrobat Bonyroba on an organic carrot farm, as the carrot plant is in the early stages of true leaf growth. A specific example of a phenotypic project undertaken with this database is crop/weed detection, for which we present the first results.

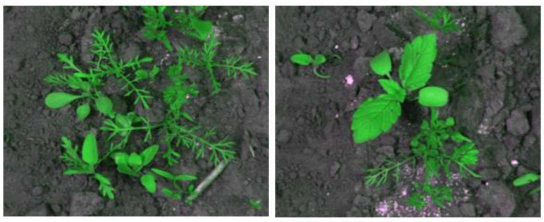

Figure 2. Sample images from dataset [23]

3.2. Data augmentation

Data augmentation (DA) is used to train the CNN model. DA techniques have been proposed in the literature, since obtaining large amounts of data is a difficult and extremely important task to obtain good results with the machine learning algorithms. Limited data is a major obstacle in the application of learning models deep, such as convolutional neural networks. Often unbalanced classes may be an additional obstacle, although there may be enough data for some classes, equally important, but classes below the sample will suffer from low class-specific precision. This phenomenon is intuitive. The proposed model implements the data augmentation techniques from simple transformations such as horizontal inversion, space increase color and random cut.

3.3. Extraction of deep features in CNN

Convolutional neural networks have different convolutional filters layers with one or more dimensions. Non-linear causal mapping is performed after every layer. Like any network used for classification, at the beginning these networks have a feature extraction phase, composed of convolutional neurons, then there is a reduction by sampling and at the end the model has simpler perceptron neurons to perform the final classification on the extracted features.

The feature extraction phase resembles the stimulating process in cells of the visual cortex. This phase is made up of alternating layers of convolutional neurons and down sampling neurons. As the data progresses through this phase, there is a reduction in dimension of layers which makes it less sensitive to the changes in input but at the same time complexity increases in features. A building block consists of one or more: i) convolutional layer (CONV) that processes data from a receiving field; ii) correction layer (ReLU), often called ReLU with reference to the activation function (rectified linear unit); and iii) pooling layer (POOL) is the compression of information by reduction of the dimensions of the intermediate image (often by subsampling) [24]. The typica architecture of CNN is shown in Figure 3.

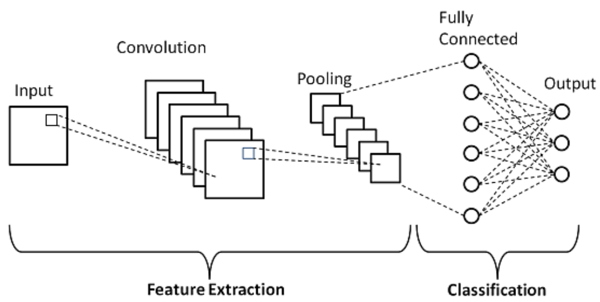

Figure 3. Deep convolutional neural network architecture [25]

The operation of convolution: in convolution operation two functions is used with real number in out arguments.

$$s(t) = \int x(a)w(t-a)da \tag{1}$$

In general, the convolution operation is represented as (2):

$$s(t) = (x * w)(t) \tag{2}$$

In convolution neural network first term (x) is represented as input argument and second term is represented as (w) kernel. The output of the convolution operation is term as feature map. Discrete data will be integrated with integral function as given in (3).

$$S(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a) \tag{3}$$

With deep learning approach input is normally represented as vector of different dimension (tensor) and the kernel is often represented as multidimension vectors. As an example, if input is image I then kernel will be 2-dimension structure which is denoted as K.

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n) \tag{4}$$

3.4. Pre-processing for second phase

This section deals with input standardization for feature extraction. The initial red, green, blue (RGB) input image is converted into gray scale. Color input separately converted RGB to Lab. The RGB color space is combination of red, green, and blue light. Lightness and the color-opponent dimensions a and b, which are based on the compressed XYZ color space coordinates. Gray scale image is used to extract texture features and Lab color space is used for extracting color moment feature.

3.5. Feature extraction

The motive of feature extraction in image processing is to express these features in numeric or symbolic form, which is called encoding. The value of this function can be real, integer, or binary. The vector consisting of the feature n represents a point in the new n-dimensional space. The steps involved in retrieving properties using the following methods:

3.5.1. Color moments

The intensity and brightness of an image is calculated by using the color moments. Standard deviation and mean are the two-color moments which are utilized for color feature extraction from the images. The histogram is taken to represent the color distribution and further standard deviation and mean represents the color moments, which are calculated [26].
Moment-1:

$$Mean = E_i = \sum_{j=1}^{N} \frac{1}{N} P_{ij} \tag{5}$$

Moment-2:

$$StandardDeviation = \sigma_i = \sqrt{\left(\frac{1}{N} \sum_{j=1}^{N} \left(P_{ij} - E_i\right)^2\right)} \tag{6}$$

3.5.2. Gray level co-occurrence matrix

The texture co-occurrence matrix considers the relationship between two pixels per time, one called a reference pixel and the other a neighbor pixel. the neighboring pixel chosen may be neighboring in any direction: e.g., east (right), west (left), north (above), south (below), or diagonally, i.e., northeast, northwest, southwest and southeast of each reference pixel. Also, the neighborhood need not be exactly 1 pixel, it can be 2, 3, or any value. Each pixel within image becomes the reference pixel, starting at the upper left corner and proceeding down to the lower right. There will of course be some particular cases, such as the pixels situated on the right margin that have no right neighbors [27].

Let's express a gray level image with the function $I(r, c)$. Let $d = (d_r, d_c)$ be the spatial relation vector. The co-formation matrix C_d is expressed as in (7) [19].

$$C_d(i, j) = |\{(r, c): I(r, c) = i and I(r + d_r, c + d_c) = j\}| \tag{7}$$

Besides the distance between the two pixels, the orientation of the pixel pair is also important. These directions can be $\theta = 0°, 45°, 90°, 135$. In Figure 4, co-occurrence matrices in three different directions obtained from a 4×4 image are seen [27].

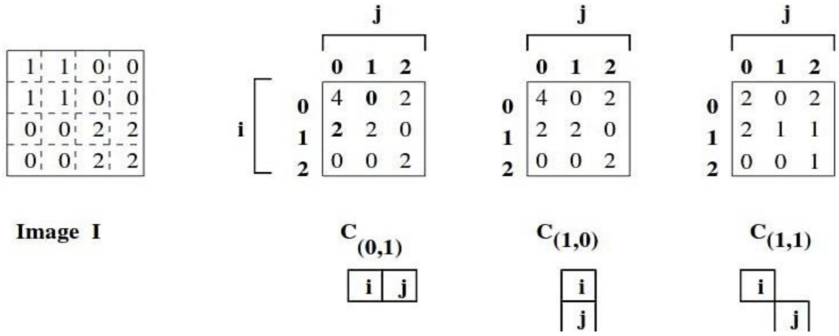

Figure 4. Co-occurrence matrices [19]

The normalized gray level cogeneration matrix N_d and the symmetrical gray level cogeneration matrix S_d are expressed as [27]:

$$N_d(i,j) = \frac{C_d(i,j)}{\sum_i \sum_j C_d(i,j)} \tag{8}$$

$$S_d(i,j) = C_d(i,j) + C_{-d}(i,j) \tag{9}$$

By using the normalized gray level co-occurrence matrix, the image properties such as the texture characteristics such as energy, contrast, homogeneity and correlation can be calculated. The properties are represented with (10)-(13) [20]:

$$Energy = \sum_i \sum_j N_d^2(i,j) \tag{10}$$

$$Contrast = \sum_i \sum_j (i-j)^2 N_d(i,j) \tag{11}$$

$$Homogeneity = \sum_i \sum_j \frac{N_d(i,j)}{1+|i-j|} \tag{12}$$

$$Correlation = \frac{\sum_i \sum_j (i-\mu_i)(j-\mu_j) N_d(i,j)}{\sigma_i \sigma_j} \tag{13}$$

where μ_i and μ_j defines arithmetic mean of the sum product of row and column GLCM matrix, where as σ_i and σ_j defines the standard deviation of GLCM matrix. Figure 5 shows correlation, Contrast, Energy, Homogeneity of texture attribute of weed image as a function of offset.

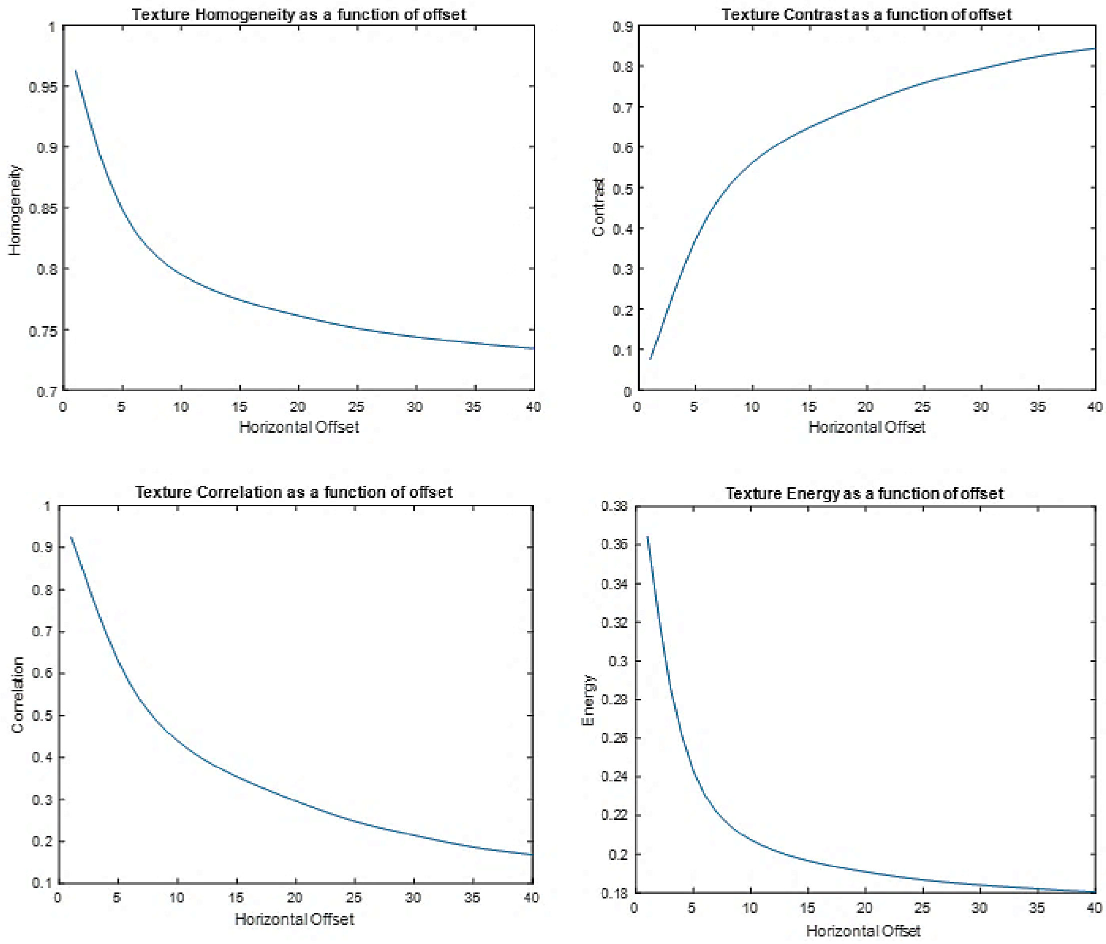

Figure 4. Texture correlation, texture contrast, texture energy and texture homogeneity of weed image

3.5.3. Gabor wavelet transform

Its 2-D image analysis, which works according directional decomposition to Gaussian windowing system where 2-D Fourier transform and four-dimension filters are used. In [28] Wavelet is constructed in isotropic Gaussian window with complex plane wave where θ represent angular values and F is the corresponding frequency [28]:

$$\psi^{\theta}(x) = \frac{e^{-\|x\|^2/2}}{2\pi} e^{-j(x^T \omega_0)} \tag{14}$$

where, $\omega_0 = F[\cos(\theta); \sin(\theta)]^T$. K represents the number of orientations within the range of $[0, \pi]$.

$$\theta \in \Theta = \left\{\frac{k\pi}{K}; 0 \le k \le K\right\} \tag{15}$$

Hence 2D decomposition of signal(x) can be represented as a dot product as (16):

$$\left\{\psi_{j,u}^{\theta}(x) = 2^{-j}\psi^{\theta}\left(2^{-j}(x-u)\right)\right\}_{\theta\in\Theta, j\in\mathbb{Z}, u\in\mathbb{R}^2} \tag{16}$$

3.6. Classification by using Bayesian optimized support vector machine

Finally, after the extraction of all images have been retrieved, the combined properties are concatenated and sorted to separate them into two classes. We work with test classes to train models and use test classes to learn models. The Bayesian optimized SVM classifier described below is used as the learning algorithm.

The SVM is designed to handle binary (+/-1) tasks. Now let's see how to solve this problem. In (17) shows the objective function [29]:

$$w_r \in H, \in^r \in R^m, b_r \in R \frac{1}{2}\sum_{r=1}^{M}\|w_r\|^2 + \frac{c}{m}\sum_{i=1}^{m}\sum_{r\neq y_1}\varepsilon_i^r \tag{17}$$

Subject to:

$$\langle W_{y_i}, X_i\rangle + b_{y_i} \ge \langle W_r, X_i\rangle + b_r + 2 - \varepsilon_i^r, \varepsilon_i^r \ge 0 \tag{18}$$

where, $m \in \{1, \dots, M\}\backslash Y_i$ and $Y_i \in [1, \dots, M]$ is the multi-class label of the X_i pattern. From the Bayes' theorem, suppose that A and $B$are two events for which the conditional probability P (B | A) is known, then the probability P (A | B) is defined as (19):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{19}$$

where $P(A)$ is the a priori probability, $P(B|A)$ is the probability of event Bdepending on the occurrence of event$A$, and $P(A|B)$ is the posterior probability. Then some utility functions are maximized in the next model to determine the next point to be evaluated, and new observations are collected to repeat until the criterion stops. Since the SVM approach uses sampling techniques for continuous parameters, it provides less accurate lossy results. This study discusses an algorithm that can set SVM parameters.

Bayesian optimization is used to tune the hyperparameters of SVM, Box constraint and sigma value are changed according to reducing the quantile error. For optimal performance of SVM it necessary to choose Kernel function, acquisition function properly [30].

$$K_{M52}(x, x') = \theta_0\left(1 + \sqrt{5r^2(x, x')} + \frac{5}{3}r^2(x, x')\right)\exp\left\{-\sqrt{5r^2(x, x')}\right\} \tag{20}$$

The covariance amplitude θ_0 and the observation noise $\nu$is tuned with the help of integrated acquisition function.

4. RESULTS AND DISCUSSION

The images utilized are obtained from crop/weed image public dataset provided by [23]. Image augmentation is performed to increase the dataset size and 60% of images are chosen for training and 40% for testing. Accuracy, precision, sensitivity, specificity and F-score are chosen as evaluation parameters.

Comparison of related works in literature with proposed hybrid feature and Bayesian-SVM classifier for weed classification are shown in Table 1.

Table 1. Result obtained under different CNN architecture with proposed hybrid features

Evaluation Parameter	VGG19	AlexNet	Inception-v3	GoogLeNet
Accuracy	91.67%	**95.83%**	93.33%	94.17%
Error Rate	8.33%	**4.17%**	6.67%	5.83%
Sensitivity	91.67%	**92.31%**	93.33%	94.17%
Specificity	97.22%	**100%**	97.78%	98.06%
Precision	92.49%	**100%**	94.14%	94.64%
False Positive Rate	2.78%	**0%**	2.22%	1.94%
F-Score	91.8%	**96%**	93.35%	94.21%

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{21}$$

$$Precision = \frac{TP}{TP+FP} \times 100 \tag{22}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{23}$$

$$Specificity = \frac{TN}{(FP+TN)} \times 100 \tag{24}$$

$$F - Score = \frac{2TP}{2TP+FP+FN} \times 100 \tag{25}$$

Where, TP=True Positive; TN=True Negative; FP=False Positive; and FN=False Negative.

4.1. Simulation results

Figure 6 shows sample image from crop/weed field image dataset showing the segmented image for extracting the region of interest, the crop and weed ground truth image from dataset and corresponding predictions where red signifies weed and green denotes crop. Also, the plots of weed probability, crop probability and background probability are represented for one sample image, X axis indicates features and Y axis indicates train feature range for each feature.

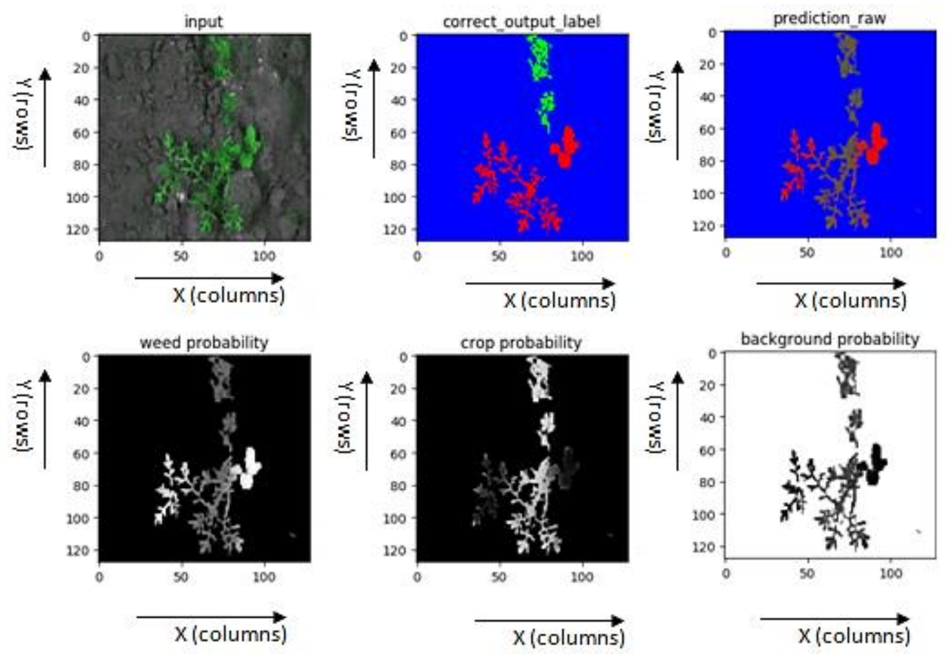

Figure 5. Segmented image to extract region of interest

Figure 7 shows different feature extraction and data distribution via box plot. There are two primary observations from this plot: i) the hybrid function of the proposed system is less deformed than in other works. The asymmetry indicates that the data may not be distributed normally. Therefore, the extracted hybrid features have a stable data distribution as a training sample from the classifier; and ii) the color and texture of crops based on hybrid features are more uniform on the graph than the color and texture of the weed group in training tasks. The average range is from 0.056 to 0.07 in the same range of hybrid characteristics. Notch plots have almost the same average weight, although it varies from class to class.

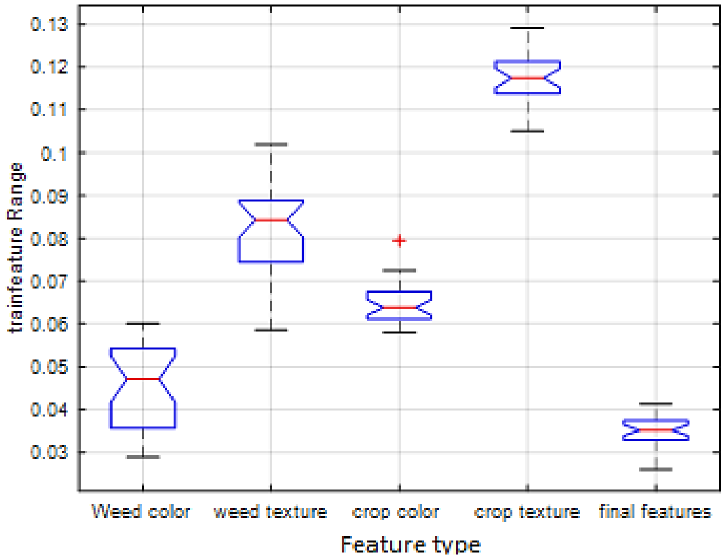

Figure 6. Range of training features extracted by hybrid method proposed

The Figure 8 shows the performance metrics comparison in terms of accuracy, sensitivity, precision and F-score. Bayesian optimized SVM produce true positive rate above 90% as compared to traditional SVM model. Whereas SVM model claims nearly 85% of true positive rate. Hence Bayesian optimized SVM will produce higher classification accuracy.

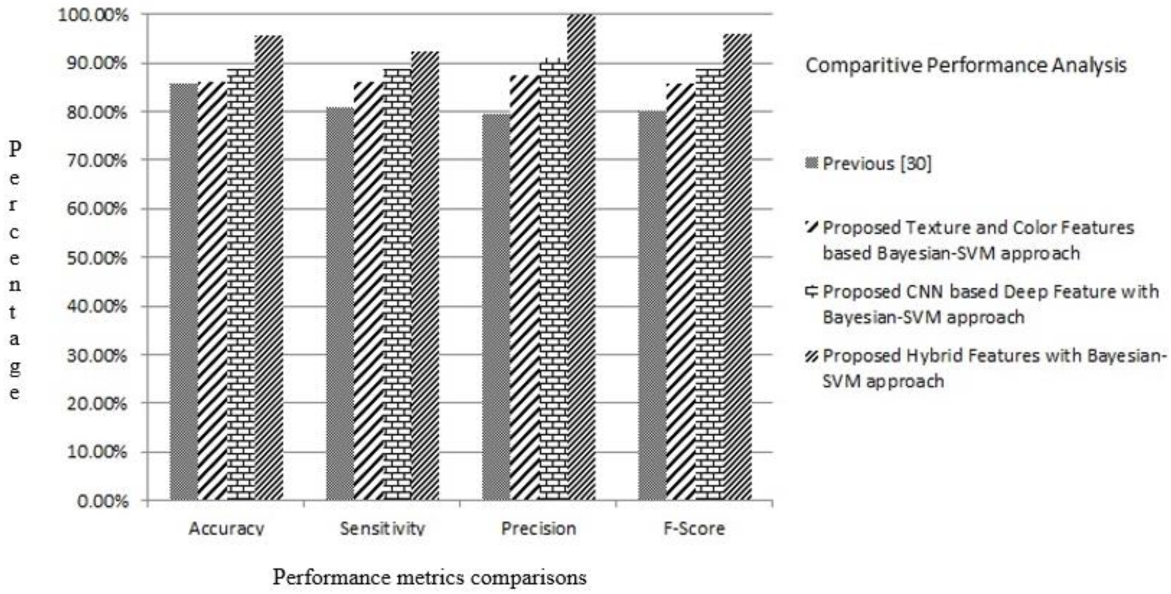

Figure 8. Performance metrics comparisons

Table 1 present the classification results with weed identification, trained with different CNN networks mainly VGG19, AlexNet, Inception-V3 and GoogLeNet respectively. The hybrid feature-based system model trained with above mentioned networks and achieved accuracy for VGG19 is 91.6% and AlexNet produces highest accuracy of 95.83% as compare to Inception V3 93.33%. For the AlexNet network system model, the average specificity, precision and F-score were higher (100%, 100%, and 96%). Higher F-score indicates better classification in classifiers.

The proposed framework is also evaluated with different features combination along with Bayesian optimized SVM. Table 2 presents comparative analysis of proposed hybrid methods, in the first proposed method texture and color features are trained and tested with SVM model achieved accuracy of 86.11%. Further in the second approach only deep features are trained and tested with 88.89% accuracy. In third hybrid model handcrafted features and deep CNN features are concatenated to make a hybrid set of features. This proposed set of features are trained and tested with Bayesian-SVM optimized classifier, where achieved accuracy is 95.83% highest amongst the other classifier.

Table 2. Result comparison

Evaluation parameter	Previous [30]	Proposed texture and color features-based Bayesian-SVM approach	Proposed CNN based deep feature with Bayesian-SVM approach	Proposed hybrid features with Bayesian-SVM approach
Accuracy	85.9%	86.11%	88.89%	**95.83%**
Error Rate	--	13.89%	11.11%	**4.17%**
Sensitivity	80.8%	86.11%	88.89%	**92.31%**
Specificity	--	95.37%	96.3%	**100%**
Precision	79.6%	87.5%	90.97%	**100%**
False Positive Rate	--	4.63%	3.7%	**0%**
F-Score	80.2%	85.95%	88.65%	**96%**

A high-dimensional dataset contains various types of weeds which increases machine overhead i.e., features for a neural network classifier. If the weight and bias values of the neural network are not optimized, then certainly it will provide low computational efficiency due to more features which is a major limitation of neural network in weed control. In the proposed work, a recognition system of weeds is carried out by means of Bayesian optimized SVM classifier. For its development, it has been considered to make a computer vision recognition system using hybridization of color moments, Gabor wavelet, GLCM and CNN based deep features; the process starts with the data acquisition, data labeling, it proceeds to pre-processing using the RGB to gray and RGB to Lab operations. Next, all the features are extracted combined trained using Bayesian optimized SVM using MATLAB tool. Once the training is completed, the desired trained model is available. Overall, by analyzing the statistical measures, we can conclude that the proposed weed detection framework provides considerably accurate outcomes.

5. CONCLUSION

This work proposes hybrid features which include the deep features from CNN and the color, texture features extracted by color moments, GLCM and Gabor wavelets for robust weed classification. The experimentation is done with 3 frame works. Initially data augmentation process has done on input image dataset and with different convolution layer wise deep feature is extracted. Further extracted features are trained by Bayesian optimized SVM classifier and result is attained in terms of precision, sensitivity, F-score and accuracy. In the next framework pre-processing of dataset images and their color and texture features are extracted by color moments, GLCM and Gabor wavelet. A hybrid feature set is constructed with color, texture and deep features. The Bayesian optimized-SVM is applied for the classification of these hybrid features to get the simulation results. The proposed method is also compared with the previous work on the same dataset and it is found that the proposed approaches outperform with the maximum accuracy of 95.83%. The future work focuses on building robust classifiers with multiclass datasets using deep learning architectures to provide better performance in terms of robustness and hardware.

ACKNOWLEDGEMENTS

The authors would like to thank Vision Group of Science and Technology, Department of Electronics, Information Technology, Biotechnology and Science and Technology, Government of Karnataka, India for Catalyzing and supporting the work.

REFERENCES

[1] M. A. Oliver, T. F. A. Bishop, and B. P. Marchant, *Precision agriculture for sustainability and environmental protection*, vol. 9780203128329. Routledge, 2013., doi: 10.4324/9780203128329.
[2] R. Lal and B. A. Stewart, Eds., *Soil-Specific farming: Precision agriculture*, vol. 22. CRC Press, 2015.
[3] T. Garnett *et al.*, "Sustainable intensification in agriculture: Premises and policies," *Science*, vol. 341, no. 6141, pp. 33–34, 2013, doi: 10.1126/science.1234485.
[4] A. McBratney, B. Whelan, T. Ancev, and J. Bouma, "Future directions of precision agriculture," *Precision Agriculture*, vol. 6, no. 1, pp. 7–23, 2005, doi: 10.1007/s11119-005-0681-8.
[5] S. H. Jeevith and S. Lakshmikanth, "Detection and tracking of moving object using modified background subtraction and Kalman filter," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 1, pp. 217–223, 2021, doi: 10.11591/ijece.v11i1.pp217-223.
[6] A. E. Smith, *Handbook of weed management systems*. Routledge, 2017., doi: 10.1201/9780203752470.
[7] E. Hamuda, B. Mc Ginley, M. Glavin, and E. Jones, "Automatic crop detection under field conditions using the HSV colour space and morphological operations," *Computers and Electronics in Agriculture*, vol. 133, pp. 97–107, 2017, doi: 10.1016/j.compag.2016.11.021.
[8] A. Bakhshipour, A. Jafari, S. M. Nassiri, and D. Zare, "Weed segmentation using texture features extracted from wavelet sub-images," *Biosystems Engineering*, vol. 157, pp. 1–12, 2017, doi: 10.1016/j.biosystemseng.2017.02.002.
[9] M. Montalvo, M. Guijarro, and Á. Ribeiro, "A novel threshold to identify plant textures in agricultural images by Otsu and Principal Component Analysis," *Journal of Intelligent and Fuzzy Systems*, vol. 34, no. 6, pp. 4103–4111, 2018, doi: 10.3233/JIFS-171524.
[10] A. Bakhshipour and A. Jafari, "Evaluation of support vector machine and artificial neural networks in weed detection using shape features," *Computers and Electronics in Agriculture*, vol. 145, pp. 153–160, Feb. 2018, doi: 10.1016/j.compag.2017.12.032.
[11] P. Lottes, M. Hörferlin, S. Sander, and C. Stachniss, "Effective vision-based classification for separating sugar beets and weeds for precision farming," *Journal of Field Robotics*, vol. 34, no. 6, pp. 1160–1178, 2017, doi: 10.1002/rob.21675.
[12] T. Kounalakis, G. A. Triantafyllidis, and L. Nalpantidis, "Weed recognition framework for robotic precision farming," in *IST 2016 - 2016 IEEE International Conference on Imaging Systems and Techniques, Proceedings*, 2016, pp. 466–471, doi: 10.1109/IST.2016.7738271.
[13] P. Lottes, R. Khanna, J. Pfeifer, R. Siegwart, and C. Stachniss, "UAV-based crop and weed classification for smart farming," in *Proceedings-IEEE International Conference on Robotics and Automation*, 2017, pp. 3024–3031, doi: 10.1109/ICRA.2017.7989347.
[14] M. Alam, M. S. Alam, M. Roman, M. Tufail, M. U. Khan, and M. T. Khan, "Real-time machine-learning based crop/weed detection and classification for variable-rate spraying in precision agriculture," in *2020 7th International Conference on Electrical and Electronics Engineering, ICEEE 2020*, 2020, pp. 273–280, doi: 10.1109/ICEEE49618.2020.9102505.
[15] H. Jiang, C. Zhang, Y. Qiao, Z. Zhang, W. Zhang, and C. Song, "CNN feature based graph convolutional network for weed and crop recognition in smart farming," *Computers and Electronics in Agriculture*, vol. 174, 2020, doi: 10.1016/j.compag.2020.105450.
[16] M. Di Cicco, C. Potena, G. Grisetti, and A. Pretto, "Automatic model based dataset generation for fast and accurate crop and weeds detection," in *IEEE International Conference on Intelligent Robots and Systems*, 2017, vol. 2017-September, pp. 5188–5195, doi: 10.1109/IROS.2017.8206408.
[17] C. McCool, T. Perez, and B. Upcroft, "Mixtures of lightweight deep convolutional neural networks: applied to agricultural robotics," *IEEE Robotics and Automation Letters*, vol. 2, no. 3, pp. 1344–1351, 2017, doi: 10.1109/LRA.2017.2667039.
[18] A. Milioto, P. Lottes, and C. Stachniss, "Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs," in *Proceedings - IEEE International Conference on Robotics and Automation*, 2018, pp. 2229–2235, doi: 10.1109/ICRA.2018.8460962.
[19] Y. Beeharry and V. Bassoo, "Performance of ANN and AlexNet for weed detection using UAV-based images," in *2020 3rd International Conference on Emerging Trends in Electrical, Electronic and Communications Engineering, ELECOM 2020 - Proceedings*, 2020, pp. 163–167, doi: 10.1109/ELECOM49001.2020.9296994.
[20] K. Zou, L. Ge, H. Zhou, C. Zhang, and W. Li, "Broccoli seedling pest damage degree evaluation based on machine learning combined with color and shape features," *Information Processing in Agriculture*, vol. 8, no. 4, pp. 505–514, 2021, doi: 10.1016/j.inpa.2020.12.003.
[21] M. Dyrmann, R. N. Jørgensen, and H. S. Midtiby, "RoboWeedSupport - detection of weed locations in leaf occluded cereal crops using a fully convolutional neural network," *Advances in Animal Biosciences*, vol. 8, no. 2, pp. 842–847, 2017, doi: 10.1017/s2040470017000206.
[22] A. I. de Castro, J. Torres-Sánchez, J. M. Peña, F. M. Jiménez-Brenes, O. Csillik, and F. López-Granados, "An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery," *Remote Sensing*, vol. 10, no. 2, Art. no. 285, 2018, doi: 10.3390/rs10020285.
[23] S. Haug, *A Crop/weed field image dataset*, GitHub, Aug. 2022. [Online]. Available: https://github.com/cwfid/dataset
[24] A. Farooq, X. Jia, J. Hu, and J. Zhou, "Knowledge transfer via convolution neural networks for multi-resolution lawn weed classification," in *Workshop on Hyperspectral Image and Signal Processing, Evolution in Remote Sensing*, 2019, vol. 2019-Septe, pp. 1–5, doi: 10.1109/WHISPERS.2019.8920832.
[25] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.
[26] F. Gulac and U. Bayazit, "Plant and phenology recognition from field images using texture and color features," in *2018 IEEE (SMC) International Conference on Innovations in Intelligent Systems and Applications, INISTA 2018*, 2018, pp. 1–6, doi: 10.1109/INISTA.2018.8466300.
[27] G. Raja, K. Dev, N. D. Philips, S. A. M. Suhaib, M. Deepakraj, and R. K. Ramasamy, "DA-WDGN: Drone-assisted weed detection using GLCM-M features and NDIRT indices," in *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPS 2021*, 2021, pp. 1–6, doi: 10.1109/INFOCOMWKSHPS51825.2021.9484598.
[28] J. G. Daugman, "Complete discrete 2-D Gabor transforms by neural networks for image analysis and compression," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 36, no. 7, pp. 1169–1179, Jul. 1988, doi: 10.1109/29.1644.
[29] S. Shahbudin, M. Zamri, M. Kassim, S. A. C. Abdullah, and S. I. Suliman, "Weed classification using one class support vector machine," in *2017 International Conference on Electrical, Electronics and System Engineering, ICEESE 2017*, 2018, vol. 2018-January, pp. 7–10, doi: 10.1109/ICEESE.2017.8298404.

[30] S. Haug and J. Ostermann, "A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2015, vol. 8928, pp. 105–116, doi: 10.1007/978-3-319-16220-1_8.

BIOGRAPHIES OF AUTHORS

Sandeep Kumar Kempegowda is presently working as assistant professor in Department of Electronics and Communication Engineering at Acharya Institute of Technology, Bangalore, Karnataka. He is a pursuing his Ph.D under Visvesvaraya Technological University, Belgavi, Karnataka, India, M.E. (ECE) from Bangalore University, Karnataka in 2010. His area of research is image processing, computer vision, machine learning and embedded systems. He is a member of ISTE. He can be contacted at email: sandy85gowda@gmail.com.

Rajeswari is presently working as Professor, Department of Electronics and Communication Engineering at Acharya Institute of Technology, Bangalore, India. She has completed her Ph.D. in the field of speech processing. Her areas of interests include speech processing, AI, computer vision and applications in the field of healthcare and agritech. She can be contacted at email: rajeswari@acharya.ac.in.

Lakshmikanth Satyanarayana is presently working as Associate Professor in Department of Electronics and Communication at Acharya Institute of Technology, Bangalore Karnataka. He has received his B.E. (EEE) and M.Tech. (CAID) from VTU, Belagavi Karnataka, India in 2002 and 2007 respectively and he has been awarded Ph.D. from Jain University, Karnataka in 2015. His area of research is signal processing, signal denoising, image processing, and noise cancellation. He is a member of IEI, ISTE. He can be contacted at email: Lakshmikanth18@gmail.com.

Siddesh Matada Basavarajaiah is presently working as Assistant Professor in Department of Electronics and Communication Engineering at Acharya Institute of Technology, Bangalore, Karnataka. He has perceived his B.E. (ECE) and M.Tech. (Power Systems and Power Electronics) from Kuvempu University, Karnataka in 2001 and 2005 respectively. His area of research is embedded systems, signal processing and machine learning. He can be contacted at email: siddeshmb@gmail.com.