

Weed Identification and Categorization in Agriculture using Hybrid Deep Learning Algorithm

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Abstract—The use of insecticides, herbicides, and fertilizer in conventional agricultural crop spraying techniques can be decreased thanks to the smart agricultural robotic system. Spraying agro-chemicals to manage weeds and get better crop output is insufficient to meet the world population's food needs. As a result, a elegant and intelligent agricultural farming system is implemented in order to boost crop yield and meet agricultural production targets. Using a mix of Convolutional Neural Networks (CNN) and Long-Short-Term Memory (LSTM), Deep Learning (DL) based algorithms are used to identify and classify weed plants in this paper (LSTM). Convolutional Neural Networks (CNN) has a distinct structure for extracting differential features from input plant images, while LSTM imply granting for combined classification optimization. In order to the proposed method is used to classify nine types of weeds, including prickly weeds, vine weeds, persistent creeping weeds, and three-leaf weeds. We conducted several comprehensive experiments and attained an average classification accuracy of 99.36 percent. The collected results suggest that the CCN-LSTM combo has much better classification capabilities than other well-known techniques.

Index Terms—Deep learning, LSTM, CNN, Classification.

I. INTRODUCTION

The Earth population is expected to grow to 9.8 billion people by 2050. As of right moment, more than 7.3 billion people are thought to live on Earth, and it is growing, according to a United Nations (UN) estimate [1]. With such a large population comes a host of problems, with proper food production being one of the most urgent. According to the UN Food and Agriculture Organization, food production must rise globally over the next few decades by 70% in order to provide food for the predictable population of 2050. There are about 2,500,000 different plant species, and 250 of them are weed plants. These weed plants have a considerable effect on the decline in agricultural production.

In essence, unwanted weed plants are byproducts of productive crops that coexist with them. Weeds inhibit the growth of desired plants, which are the crop's essential and primary products, because they devour water and plant nutrients and minerals. In order to solve this issue, this study article performs precise and trustworthy weed and desirable plant detection. We employ CNN and LSTM models to carry out the detection of weed plants. The identification and separation of weed plants is based on two key factors: life span and ecological affinities. Lifespan: Lifespan weeds can live for more than two years and are often found in uncultivated places. They can

kill seeds, underground stems, roots, rhizomes, tubers, and other plant parts. Ecological affinities: These weeds are cultivated for a variety of purposes, and in semi-aquatic conditions, they germinate as seeds. The most frequently studied topic for enhancing crop productivity and controlling weeds is agricultural mechanization [10, 11]. An essential component of the intelligent sprayer system for boosting agricultural output is the classification of weed plants [12]. Agricultural pesticides provide advantages like enhanced agricultural yield, but they can also have harmful effects on human health and the environment [13, 14]. Precision farming equipment is necessary to prevent the overuse of herbicides and pesticides [15, 16].

Weed identification is a fascinating area of study for data scientists, and many machine learning-based techniques have been reported [17]. Numerous studies use computer vision algorithms to identify and categorize weed and agricultural plants [18, 19]. There are a lot of hand-crafted, deep learning-based models that have contributed a lot to the literature [20–25].

There have been many different classification approaches for weeds, such as colour categorization techniques for identifying perennial weeds [18], Sugar beet plants and weeds may be distinguished using a deep convolutional neural network (DNN), CNN-based technique [29], Gabor wavelets and neural networks [31], Kalman filter [32], artificial neural networks and decision trees, hyper spectral imaging with wavelet analysis [34], supported by Skovsen et al. [39], among others To identify weeds, Tang et al. [40] combined a K-Means feature with CNN. Tang et al. [40] used CNN's K-Means function to identify weeds. Support vector machines and artificial neural networks were presented by Adel et al. [41] in order to identify weed plants using shape-features.

These techniques have produced astounding results and shown tremendous progress in the agricultural industry. To increase the categorization accuracy of the weed plants, however, efficient and sophisticated classification methods are needed. Categorization of weeds is particularly challenging since, during late growth stages, the leaves of crops and weeds frequently overlap [41]. In this study, a deep learning-based hybrid approach made up of CNN and LSTM is employed to identify and classify weed species. The D-CNN-main LSTM's objective is to develop a self-learning system for weed species classification accuracy improvement by learning characteristics.

A. Techniques for Classifying Weeds

Long short-term memory (LSTM) and convolutional neural networks (CNN) models are suggested in a recent research study for the categorization of weed plants. The suggested paradigm consists of three main steps. With CNN as the first step in feature capture, LSTM as the second step, and fully linked layers as the third, the features are produced. The subsections that follow go into further detail.

Convolutional Neural Network (CNN)

Deep neural networks (DNNs) are networks of neurons connected by weighted edges. Each edge and neuron is given an activation value and weight respectively. The three core elements of CNN are the convolution layer, max-pooling layer, and fully connected layer. Convolution layers are one of the CNN's activities, can carry out a convolution operation on an array of data and pooling algorithms. In addition, a rectified linear unit serves as an activation function (ReLU). CNN models' capacity to automatically extract characteristics, in particular, expands the breadth of research applications for which they can be used [42]. Modern deep CNN models that have been successfully used in numerous fields include ResNet-50, GoogLeNet [43], Inception-v3, ResNet-50 [44], Alex Net and VGGNets [46]. These are just a few examples. In 2012, Comparing AlexNet to earlier models, classification error rates was much lower [42]. In order to drastically reduce the error rate, the winning technique (GoogLeNet) was used as an upgraded model in 2014 [43]. The CNN model's layers include:

Convolution Layer: The convolutional layer, which creates new images called feature maps, is the primary layer of CNN. Figure 1 depicts the general architecture of CNN models. The feature map emphasizes the distinctive elements of the original image. When a 2D input picture of a weed plant is used, such as a matrix $A_{n1 \times n2}$ and the clean matrix $X_{m1 \times m2}$, where $m1 \times n1$ and $n2 \times m2$, the matrix $B = A \times X$ is produced because of the 2D convolution of A with X and may be characterized mathematically as:

$$H = A * X \rightarrow H_{i,j} = \sum_{k=1}^m \sum_{l=1}^n A_{i+k-1,j+l-1} X_{k,l} \quad (1)$$

Pooling Layer: The image's size is decreased by the pooling layer by combining nearby pixels in a particular area of the image into a single representative value. Mean pooling or max-pooling are the two most popular types of pooling layer. In this study, max pooling is used, and its mathematical definition is:

$$H_{i,j} = \max\{A_{i+k-1,j+l-1} \forall 1 \leq k \leq m \text{ and } 1 \leq l \leq m\}-(2)$$

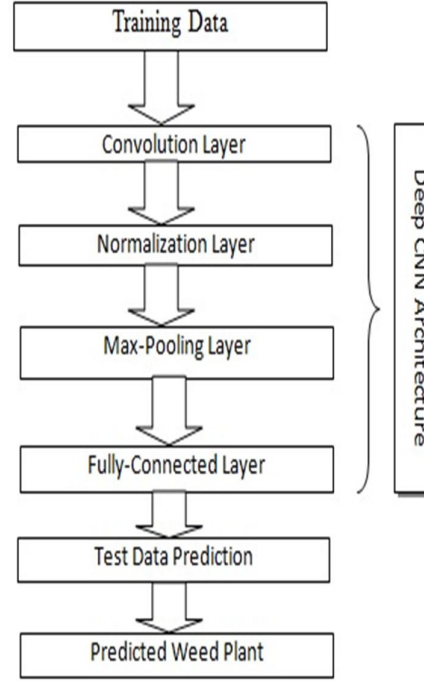


Figure 1. Deep learning algorithms for weed identification

Long-Term Short Memory (LSTM)

In this article, weed plant characteristics are extracted using the peephole LSTM model. W and b are the model parameters, the sigmoid function is taken into account, and gt is the nonlinear transformation of the inputs. The internal state of the LSTM component is stored in memory cell ct (where t denotes step time), with the LSTM's inputs and outputs being represented by xt and ht , respectively. The input gate it , output gate ot , and forget gate ft are three additional gates in the LSTM. The mathematical formulation of the LSTM approach is as follows:

$$\begin{aligned}
 it &= \sigma(Xi[ht-1, xt, ct-1] + bi) \\
 ft &= \sigma(Xf[ht-1, xt, ct-1] + bf) \\
 ot &= \sigma(Xo[ht-1, xt, ct-1] + bo) \\
 gt &= \tanh(Xo[ht-1, xt] + bg) \\
 ct &= ft \odot ct-1 + it \odot gt \\
 ht &= ot \odot \tanh(ct)
 \end{aligned}$$

Here ' $\odot$ ' denotes the Hadamard product. The memory cell is the essential idea in an LSTM network it enables long-range dependency learning from input sequences and state storage across time.

II. PROPOSED ALGORITHM

The proposed algorithm is CNN-LSTM; it is combination of CNN and LSTM algorithms results in outstanding weed plant classification accuracy. In a wide range of applications, pre-trained DL networks are frequently used. This is also a typical technique in the DL field. In this study, we created a weed classification system that we trained using information from more than 17,000 weed plants. The DL is made up of multiple layers, including a batch normalizing layer and a convolution layer. The max-pooling layer, rectified linear unit layer, LSTM layer, and soft-max layer were used to categorize the weeds. This strategy is seen in Figure 2.

Initially, the recommended CNN-LSTM based design had four convolutional layers. The first convolutional layer had a 1010 frequency-time filter. The second layer 99 filter, third layer 54 filters, and fourth layer 43 filters operate similarly. We employed batch normalization and adjusted linear units for each convolutional layer. Three different size-pooling layers are applied to each of the convolutional layers. A forget gate, a cell, an input gate, and an output gate comprise an LSTM unit. [49].

The cell's primary function is to store data for arbitrary time intervals, and each of the three gates regulates the flow of information into and out of the cell. The four layers of the 32-unit LSTM network used in this study. The LSTM output data is modified using a flatten layer, which also acts as a communication link between the dense layers.

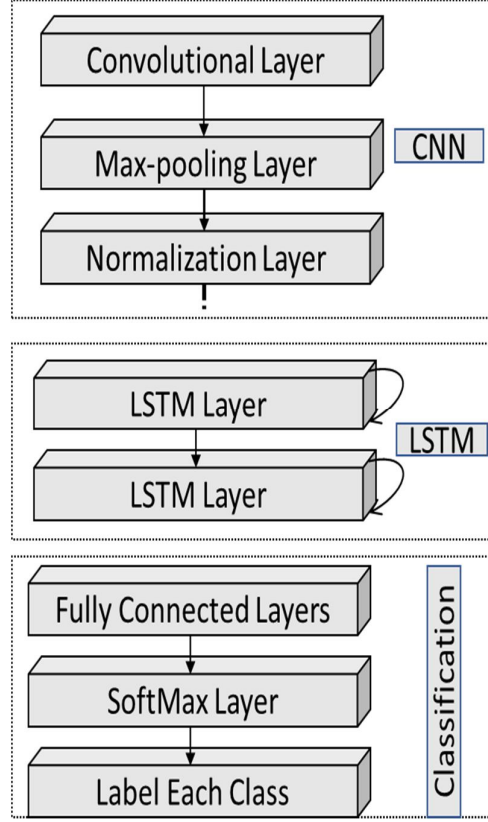


Figure. 2 The suggested classifier is based on LSTM and CNN

III. EXPERIMENTS

A. Weeds Dataset

An Australian research team initially compiled the dataset [50]. They gathered in various parts of northern Australia. To attain the requisite variety and generality of the dataset, they developed two key goals. First, the collecting of dissimilar crop species, which totals roughly 1,000 photos, aids in high-complexity CNN training if large labeled data sets are required. Second, divide them equally between positive and negative locations. By guaranteeing that targets can be distinguished from their natural backgrounds, it also helps prevent over-fitting existing models to scene-level visual features. Finally, professional analysis was required to each image regarding whether it contains a specific weed species or not. The name of the weed and representation is shown in Table 1, Figure 3 represents the weed plants and their distributions and Figure 4 represents the images of the weed plants.

During the training and validation process, over fitting has been reduced by using the data augmentation technique [51]. A technique for creating more training and validation data from the present data collection is called data augmentation. The data augmentation technique included the use of flipping, color rotating, zooming, horizontal and vertical shift, modifying the brightness level, and cropping to create new weeds photographs for the training set. (OpenCV) and another deep learning algorithm have been applied as augmentation. For instance, Fig. 5 displays the virtual, randomly created graphics. The range now lies between [0.8, 1.2] after each picture has been zoomed at random by $\pm 20\%$. In the $\pm 360^\circ$ range, rotation augmentation has been done at random. Each image's colour has been randomly changed by $\pm 20\%$. The picture data contains a Boolean horizontal or vertical flip parameter that indicates the flip augmentation. Each picture has been shifted roughly both vertically

TABLE I. WEED PLANTS REPRESENTATIONS

Name of Weed	Representation
Chinee apple	W1
Snakeweed	W2
Prickly acacia	W3
Lantana	W4
Parthenium	W5
Parkinsonia	W6
Negatives	W7
Siam weed	W8
Rubber vine	W9

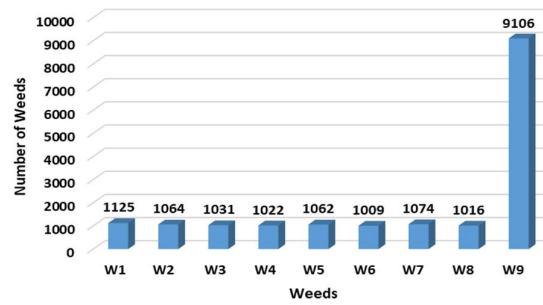


Figure 3. Weed plants and their distributions

and horizontally $[-0.5, 1]$ thanks to shift augmentation, which involves shifting all of the pixels in a picture in one direction, such a horizontal or vertical shift.

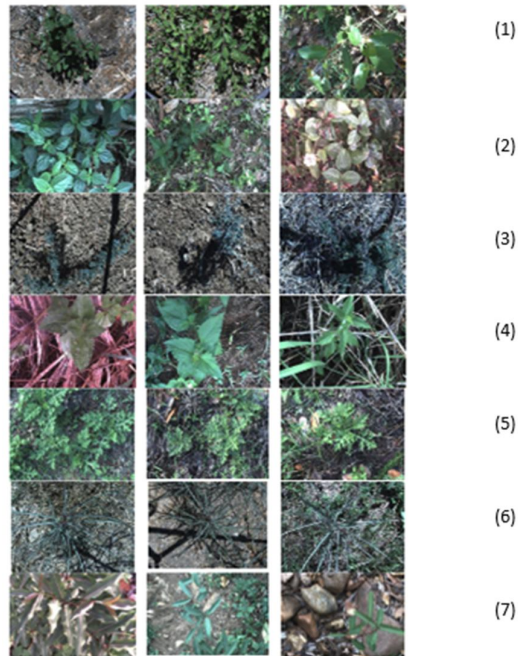




Figure 4. (1) Chinese apple, (2) Snakeweed (3) Prickly Acacia (4) Lantana (5) Parthenium, (6) Parkinsonia (7) Negatives (8) Siamweed (9) Rubber wine

The image is randomly brightened, darkened, or both as part of the brightness augmentation process. Brightness enhancement has been used in this study between [0.5, 1.5]. Each image in this experiment has its dimensions randomly reduced from 256 by 256 to 224 by 224.

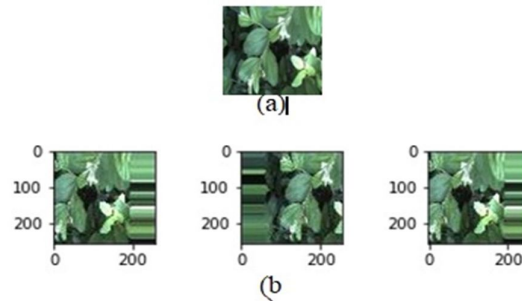


Figure 5. Training Actual image (a) and the images were produced using the augmentation technique. (b)

A deep learning network must learn and be validated at a certain learning rate. This study used an finding the best learning rate to maximize the effectiveness of the learning process. The optimizer may exceed its target value if the learning rate is too high or become wickedest divergent, and if it is too low, the optimization process takes longer to learn. The effectiveness of the model was evaluated using the 5-fold cross-validation technique. The data sets were divided into two groups, with 40% used for validation and 60% utilized for training. Each of the five epochs is used to train the model 30 times, and each training and validation's accuracy of validation is reported. The HP computer with the following specifications was used in the test: Intel(R) Core TM i5-4790 CPU, Windows 64-bit OS and 16GB RAM.

IV. RESULTS AND DISCUSSION

We used an amalgamation of CNN and LSTM techniques to categorize the weeds shown in Table 1 by using their characteristics. Table 2 displays the outcomes of the suggested technique. It explains how accurately each weed is classified. The obtained results are encouraging because, with the exception of negative weeds, their average classification accuracy is greater than 98%. We reached 100% accuracy in two weed scenarios, Parkinsonia and Prickly acacia. It demonstrates how effective the suggested method is in accurately classifying weeds. The reason for this is because while CNN gives features from the data sets, LSTM assists in producing textual descriptions from picture data sets. Additionally, LSTM interpreters are highly effective in classifying the weed data sets, as is this ensemble technique. The findings give us the notion that all weeds must be categorized for better agricultural performance.

The use of deep learning techniques on agricultural data sets will aid in the development of farm supervision systems with true AI systems, offering solid recommendations and insights for increasing agricultural crop production and protecting them from undesirable crops that could lower crop productivity.

Although the model iterates repeatedly in this case, the categorization rate was established after the 90th iteration. Here we used the 5-fold cross-validation technique mendacity at the counselled system, as illustrated in Figure. 6 and Figure.7, to track training and validation progress. The CNN and LSTM models are anticipated to be even more common on farm data sets in the future, improving productivity.

The suggested work has some drawbacks, including the need for high-end calculation time on both methods with or without augmentation due to large data sets. To get around this, we advise the prospective researcher to divide the data set into epochs before training it, then use each time as a training set to verify the classification accuracy. Where a different prediction model will be produced for each period.

TABLE II. THE CLASSIFICATION ACCURACY OF NINE WEEDS PLANTS CONFUSION MATRIX

Name	W1	W2	W3	W4	W5	W6	W7	W8	W9
W1	99.3	0.02	0	0.1	0	0.3	0.5	0.09	1.01
W2	0.13	99.2	0	0.01	0	0	0.3	0.03	0.03
W3	0.01	0.02	100	0.02	0	0	0.04	0	0
W4	0	0.01	0	99.8	0	0.1	0.06	0.03	0.01
W5	0.2	0.03	0	0.03	100	0	0.03	0	0.53
W6	0.1	0.05	0	0	0	99.4	0.01	0.4	0.14
W7	0.02	0.21	0	0	0	0	99	0	0.03
W8	0.23	0.06	0	0.04	0	0	0.02	99.4	0.15
W9	0.01	0.4	0	0	0	0.2	0.04	0.05	98.1
Average (%)	99.3	99.2	100	99.8	100	99.4	99	99.4	98.1

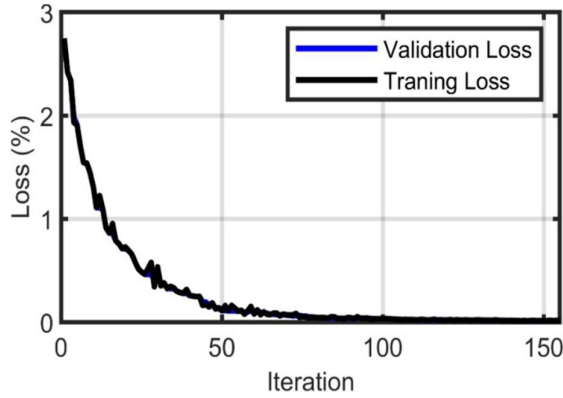


Figure 6 The proposed CNN-LSTM method Classification Error

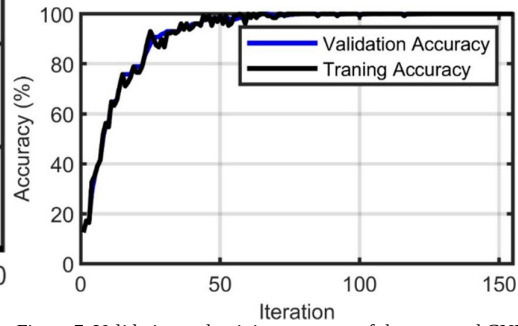


Figure 7. Validation and training accuracy of the proposed CNN-LSTM method

A. Performance Comparison

In order to justify the proposed method, the recorded findings are compared against recently revealed methodologies using the same data sets. The results of the comparison are displayed in Table 3. The nine weed plants were classified using the Inception-v3 model, with an average classification accuracy of 95.1%. Nine weed plants were used to test the ResNet-50 deep learning model, with an average accuracy of 95.7% [50]. The suggested strategy outperforms Both testing methods using Inception-v3 and ResNet-50 need data augmentation as shown in Table 3. A workable method for improving the dataset and network performance in weed data categorization is offered by the augmentation strategy. As a result, we carried out research both with and without augmented data. The reported accuracy of with data augmentation is 99.36%, and without data augmentation is 96.06 %, as shown in Table 3 and Figure 8. While the classification accuracy is somewhat greater without data augmentation, the proposed strategy performs better with it. However, we think that there is space for improvement in categorization when studies are carried out without enhancement findings.

TABLE III. COMPARISON OF CLASSIFICATION ACCURACY (%) THE WEED PLANTS WITH THE CURRENT APPROACHES

Name of the Weed	Inception-v3	ResNet-50	The Proposed Method	
			With	Without
Chinne Apple	85.3	88.5	99.3	97.3
Snake weed	88	88.8	99.4	93.9
PricklyAcacia	92.8	95.5	100	96.4
Lantana	94.4	95	99.2	95.5
Parthenium	94.9	95.8	99.8	98.1
Parkinsonia	96.8	97.2	100	97.7
Nagatives	97.2	97.6	98.1	95.2
Siamweed	97.6	96.5	99	94.8
Rubberwine	93.1	92.5	99.4	95.7

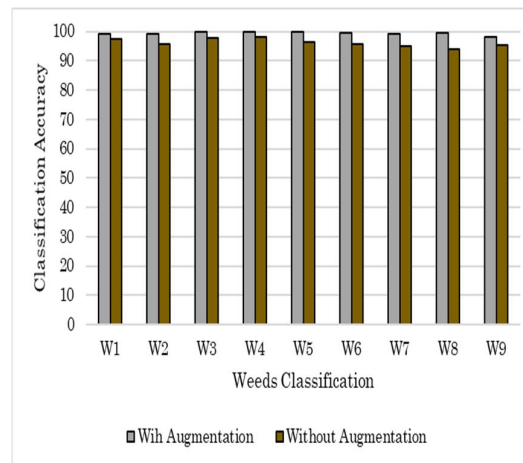


Figure 8. Comparisons between outcomes with and without augmentation

V. CONCLUSIONS

In this study, a novel system based on convolutional LSTM was created for the classification of weed plants. Although a number of approaches based on computer vision have been put forth for classifying plants, this research area still needs sophisticated and automatic classifiers. The suggested method delivers excellent weed plant identification and categorization capabilities. The algorithms have been put to the test in a number of trials, and the results point to the proposed schemes as being a significantly better categorization method. For weed plant identification, commercial solutions are also required. Commercial robotic-based solutions for weed identification and pesticide application will be developed in the future.

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