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ARTIFICIAL INTELLIGENCE FOR WEED DETECTION - A TECHNO-EFFICIENT APPROACH

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Abstract

Technology is improving the ways, methods and approaches many old and tedious tasks are being performed such that the thoughts of the in-existence of these present technologies about some decades ago may negatively change one's mood. The emergence of Artificial Intelligence has significantly improved almost every aspect of human life, considering the enormous roles it has begun to play in agriculture, researchers and scientists are seeking better ways of improving and ensuring optimal efficiency of the developed systems. This paper gives an insight into the application of Artificial Intelligence (AI) as the best techno-efficient approach for weed detection. A collection of fifty (50) various research works reported by researchers on weed detection in the years ranging from 2012 to 2020 were sampled and examined. A streamlined classification and categorization was performed based on their degree of relevancy to the study. The adopted methods, nature of inputs, processing methods and result obtained from the various study were considered. The roles played by the application of intelligent systems were highlighted with a view of broadening reasoning and channelling future researches towards developing better and more techno-efficient intelligent systems to aid in agricultural related activities. Research findings indicate that technological improvements towards the introduction and usage of Artificial Intelligent (AI) systems will result in a more techno-efficient method for weed detection in agriculture.

Keywords:

Artificial Intelligence, Agriculture, Robotics, Machine Vision, Thresholding, Weeds Detection, Machine Learning

1. INTRODUCTION

Agriculture as one of the oldest branches of science dealing with the cultivation of crops and rearing of animals for both human and industrial consumption has been through different stages of technological development throughout the ages due to man's quest to reduce human intervention and improve crop yield. The invention of machineries such as tractors, harvesters, planters, sprayers etc. is part of man's effort towards improving agriculture [4].

Although, these machines have greatly impacted agriculture [24], but are limited in performing special intelligent functions such as determining ripe fruits or crops to be harvested, selecting the most suitable soil for crops, application of the right quantity of water during irrigation and detection of weeds during weeding process .

Weeds are generally found among crops, they compete with other plants for resources such as water, nutrients, air and space thus limiting the growth of desired plants. Improper growth of desired plants will lead to poor crop yield [15] or harvest and in turn have a diminishing effect on the economic status of the farmer.

However, since farmers dislike to record loss in the overall output of their farm produce and monetary investment, they seek ways to eliminate the presence of weeds and its damaging effect on desired plants through the application of herbicides and other known cultural means [9]. These conventional methods used do not accurately eliminate weeds as they still have a significant level of damaging effect on the desired plants. In order to ensure preciseness and improve accuracy in weed detection; farmers, agricultural organizations, research institutes are now incorporating artificial intelligence principles through various technological devices and gadgets to aid in the process.

The application of technological gadgets embedded with Artificial Intelligence (AI) in agriculture is currently yielding significant results in weed detection and improving crop yield [1], thus necessitating the need to consider the technological roles of Artificial Intelligence in Weed detection.

The rest of the paper is organized as follows. Section 2 is a presentation of surveyed and related existing work. The methods and procedures employed in this research work are detailed in section 3. The experimental results are presented and compared in section 4. Section 5 concludes the research work and mentions the future direction.

2. RELATED WORKS

Machines or devices which have the ability to incorporate intelligence into applications being handled are often termed intelligent systems. They usually possess artificial intelligence which enable them perform complex automated tasks and function like human experts [6]. Different techniques, methods and paradigm are deployed to incorporate intelligence into technological systems to ensure that connected components function appropriately.

Many and more researches are on-going with the sole aim of improving and adopting better techniques to aid in weed detection and control. The major and common approach applied in the researches is the detection method using image processing and filtering technique.

Latha et al. [15] proposed a K-means clustering method for weed detection using inter-row and inter-plant technique to detect and control weeds on a corn field with varying results each time the method was deployed.

Michelle et al. [18] in their research detected weeds by combining image processing technique and components labelling method with aspect ratio to compare heights and width of images for weed detection and control. Furthermore, a more efficient method for weed detection and control was developed and implemented by Shraddha et al. [28]. The developed intelligent system consists of a RF-transreceiever which transmits wireless signals based on the input received using MATLAB to filter and segregate weed colour to a robotic sprayer for efficient application of fertilizers.

Radhika and Roopa [22] also presented a machine vision system for weed detection in vegetable crops using image filtering to extract colour and area features with special consideration to the illumination level of the captured area to aid efficient analysis.

Recently, the BASF, a German chemical company and the largest chemical producer in the world acquired the Xarvio scouting app which enables farmers to spontaneously identify weeds or diseased infected plants by taking snapshot of a given farmland. The application possesses over 150,000 images of weeds and diseased plants hosted on a remote server to aid in fast comparison and assists in detecting weeds [12]. The company boasts over 90% accuracy level on the images tested for weed identification on various farm lands.

Sandeep et al. [27] combined segmentation procedures with Convolutinary Neural Network (CNN) and Image processing technique to segregate weeds from crops in a carrot plantation. A collection of RGB weed data was kept in a database and implemented with Python Programming language. The method resulted in 95% accuracy in CNN adopted Classification and weed detection.

Pejman et al. [21] in their assessment of the application of Artificial Intelligence technique in the classification of weed proposed a scattering transform which denotes a method of weed detection in culture crops of high density based on energy contrast. A synesthetic data set was provided and used to train their model which showed an accuracy of 85% when deployed on real data.

Adel and Abdolabbas [2] integrated several shape features with Machine learning techniques - Support Vector Machine and Artificial Neural Networks to aid in the precise detection of weed on a sugar beet field. Results obtain accurately reflected the ANN adopted correctly classified 92.5% of the weed at an accuracy level of 92.9%. However, a higher accuracy of 95.00% was observed when the Support Vector Machine was used as classifier though with 93.33% of weed correctly classified. A research conducted by Adam Davis, Head of Crop Sciences department and his team at the University of Illinois led to the development of Killer robots to stop the growth of weeds [11]. Grinblat et al. [7] identified species of legumes using Deep Convolutional Neural Network for classifying leaf veins on morphological patterns.

Furthermore, an accuracy of 92.5% was derived when Tang et al. [30] applied linear methods of scanning with projection at varied illumination levels and conditions for specific spraying on weeds. Plant leaf features extraction for recognition was performed by Lee et al. [14]. In a bid to rapidly obtain and identify weed during a real time precision spraying process, Xu et al. [32] developed a system optimizing Absolute Feature Corner Point (AFCP) algorithm. The algorithm merged absolute corners to identify crop and weed positions. Key parameters in this model are the weed pressure and cluster rate. Validation done based on the real time images captured on farmland reached an accuracy level of 90.3%, thus revealing that the AFCP algorithm is applicable for real time weed detection and management.

3. METHOD AND PROCEDURE

Methodology describes the procedural analysis for carrying out a research work. In this research, a bibliographical analysis of the study under consideration was performed in three major stages:

- ***Collection of Related Work*:** This process involves an online keyword search of research papers, scholarly articles and international journals on Weed detection and Artificial Intelligence from scientific databases, Google Scholar and other scientific indexing sites. A total of 50 papers from various research works were derived from the search terms. In a bid to determine the recency of the research work to the study under consideration, year of publication selection criteria was adopted. Ten papers published in the years less than 2012 and which do not depict the nature of the study were filtered out, thus leaving the researcher with 40 papers to work with.
- ***Performing detailed analysis and review of selected papers***: In this stage, the forty (40) selected research papers from the initial step were further analyzed to determine their suitability for the study to encompass the integration of Artificial Intelligence through the adoption of various Machine learning techniques for weed detection. A total of ten (10) papers were also filtered out as they do not meet with the requirements. The remaining thirty (30) papers which met the requirement were then detailed reviewed and used for the study.
- ***Analysis, Comparison and Evaluation based on Selected Metrics***: This step involves critical analysis, comparison and evaluation of developed systems based on some selected metrics. Selected metrics included in this research are: degree of accuracy, AI techniques adopted, type and volume of data used, pre-processing methods, Complexity of operation and degree of techno-efficient ability.

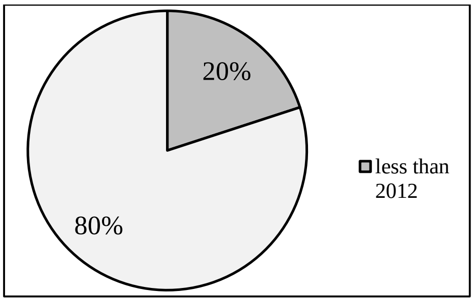

Fig.1. Classification of collected related researches filtered by recency

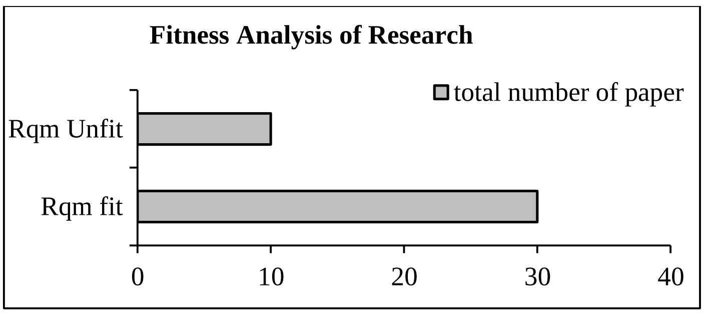

Fig.2. Classification of collected related researches filtered by recency

The method mainly adopted by researchers for weed detection requires many processes which are grouped into stages [17]. In this paper a series of referenced images are used to illustrate the numerous stages towards identifying, detecting and selecting of weed during the weeding process. The Fig.1 and Fig.2 show the initial classification of collected related research work filtered by recency and requirement fitness.

3.1 PROCEDURES

The procedures employed are categorized into four namely:

1. Image Capturing
2. Image Processing
3. Image filtering
4. Image Classification.

3.1.1 Image Capturing:

The initial stage also referred to as the data collection stage involves on site visitation to the field or farmland where the weed are to be identified and detected. Numerous images of the area are captured with the aid of a high resolution camera either connected to the tractor, moving farm equipment or manually captured at different projection perspective [8] (i.e. top, front or side view) and at various illumination level which is characterized by the condition of the day (i.e. morning, afternoon or evening) [26].

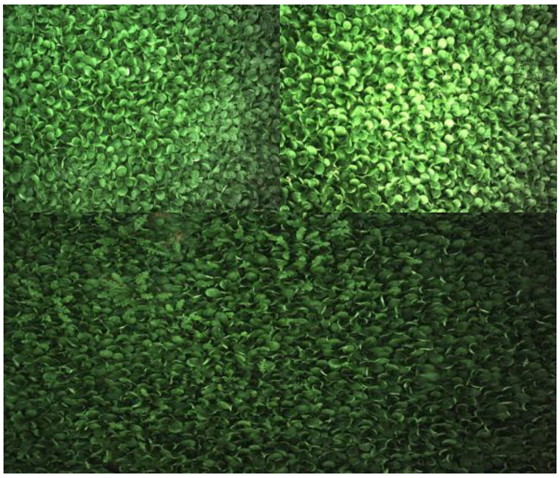

Fig.3. Captured images of land before and after background removal [21]

The Fig.3 is a screen shot of selected captured images of high density weed performed by a JAI manufactured camera of 20 M pixels with a spatial resolution of 5120 x 3840 pixels, mounted with a 35 mm objective camera of 1024 resolution mounted on a tractor. Further processing is performed on images by Artificial Intelligence (AI) embedded systems to identify and detect weeds.

3.1.2 Image Processing:

Processing of images inputted to the system commences at the second (data preparation) stage as shown in Fig.4. Image validity check is carried out on the images to ensure they meet with the required specification proposed by the system else an image conversion is necessitated to meet the required image format.

Software tools such as the MATLAB, Orbit, Image *J*, and Ilastik are used in processing the images. The back ground of the captured image which could hinder effective detection is removed using any of the appropriate segregation (colour or image –edge) technique as it had been applied and shown in Fig.5(a).

Images were later subjected to both grey and binary conversion processes to hasten other processing actions such as filtering, texture analysis, segmentation, noise removal and thresholding until a desired result is obtained. The Fig.5(b) is a screen shot of a grey transformed image used to improve weed detection.

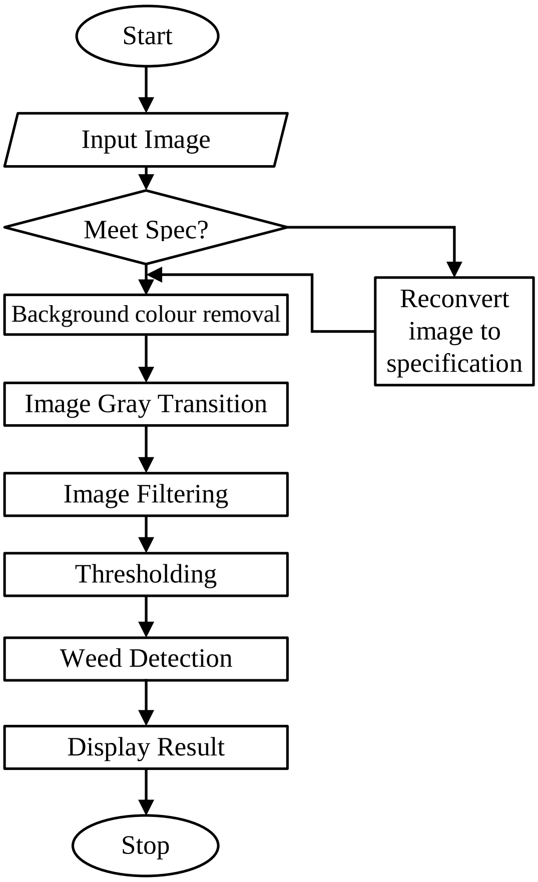

Fig.4. Flowchart for weed detection system

Fig.5(a). Captured images of land before and after background removal [18]

Fig.5(b). Gray transformed image of weed detection system [23]

3.1.3 Image Filtering:

A list of filtering methods which can be used for sharpening, smoothing or removal of noise in images abound [15]. Most literatures reviewed have employed the Gaussian filtering method because of its efficient noise removal and image smoothening ability. However, the choice of image filtering method is dependent on the nature of input image and the intended result to be derived from the images.

The Gaussian filtering method can be denoted mathematically as given below:

$$G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)}{2\sigma^2}} \tag{1}$$

where z = grey level, μ = mean and σ = standard deviation

Shape factors (*S.Fact*) techniques adopted for filtering various types of plants requires a detailed description of plants. Formulas for these techniques are represented in Eq.(2) – Eq.(4), respectively.

$$S.Fact1 = Area/((Length\ of\ axis)^3) \tag{2}$$

$$S.Fact2 = (4\pi\times \text{Area})/((\text{Perimeter})^2) \tag{3}$$

$$S.Fact3 = (4\times Area)/((\pi\ .length\ of\ axis_1)\times(length\ of\ axis_2)) \tag{4}$$

A more efficient technique is the application of Fourier's descriptors for easy extraction of shape features and robustness to noise as depicted in Fig.6. The computation of centre-boundary distances and edge detection of the binary transformed images were performed. The Eq.(5) denotes the Euclidean formula used for centre boundary calculation.

$$CbD(n) = \sqrt{\left(x(n)-x(c)\right)^2 + \left(y(n)-y(c)\right)^2} \tag{5}$$

where $CbD(n)$ represents the distance of the nth boundary point from the object, the points $(x(n),y(n))$, $(x(c),y(c))$ are coordinates of n^{th} boundary points and objects centre respectively.

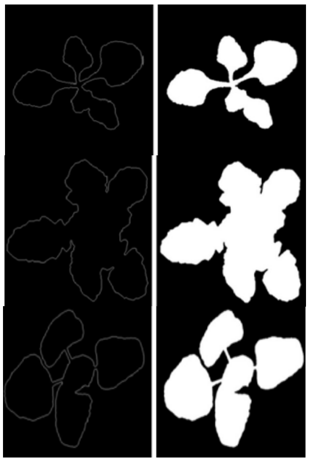

Fig.6. Detected images of selected weeds from binary images [2]

For optimal result to be derived a threshold value is set [16] and results obtained can later be deployed to ultimately classify and precisely detect weed or be used as input into an AI sensor device which can process the input to locate and apply the necessary herbicide on the weeds only.

3.1.4 Image Classification:

Numerous primitive approaches have been adopted in the classification of crops and weed before the introduction of artificial intelligence techniques. These primitive approaches are brain tasking, time consuming and less efficient with incorrect result often times. However, the introduction of Artificial Intelligence and machine learning techniques has helped to combat the challenges, thus yielding better predictions and a more accurate result.

A major technique for accurate classification is the application of Artificial Neural Network (ANN). It combines statistical technique with machine learning to imitate human intelligence in weed classification. Its variants structure as shown in Fig.7(a) and Fig.7(b) is modeled into three basic layers; input, hidden and output layers respectively consisting of interconnected nodes. Each node act as a processing unit which can be modified with links showing the relationship between the nodes.

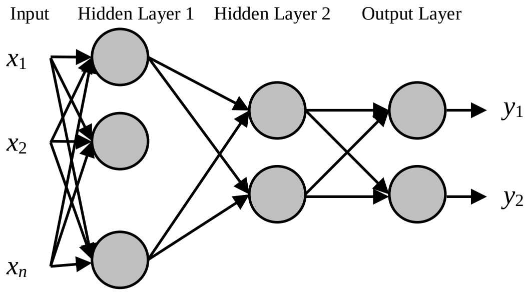

Fig.7(a). Feedforward ANN structure with dual outputs (y_1 and y_2)

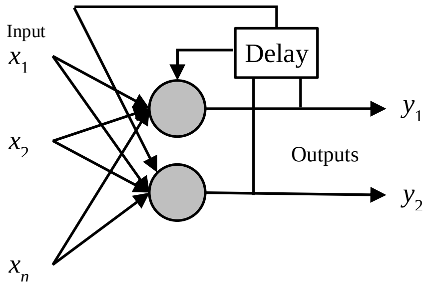

Fig.7(b). Recurrent ANN structure with dual outputs (y_1 and y_2)

These models help to classify weed by learning from a collection of supplied similar or related data set, generate a model whose performance can be improved by continuous training. Testing and validation can also be performed by supplying a new set of data for which classification can done based on the information already extracted from the training data. Every data sample for use in learning consists of an input vector $x(n)$, a neuron (k) which gives the corresponding output $Y(n)$. The output is compared with a desired output (ω) to calculate the Extent of error (*E.err*). The main aim of this computation is to minimize the Error energy value (*E.eng*).

$$Y(n) = f\,(x_1w_1+x_2w_2+\ldots.+x_nw_n) \tag{6}$$

$$E.err(n) = (\omega)n - Y(n) \tag{7}$$

$$(E.eng) = 0.5{*}x((\omega)n{-}Y(n))^2 \tag{8}$$

where n = number of steps in the iterative process and W is the input weight.

This error value derived is also used to tune the input weight in order to generate an output with close proximity to the desired output (ω) in a step wise manner. Weights are adjusted following the Widrow-Hoff rule in Eq.(9) and the new updated value of the new synaptic weight calculated as given in Eq.(10).

$$\Delta w(n)=C.(E.err(n))\ X(n) \tag{9}$$

given that C = Numerical constant

$$w(n+1)=w(n)+\Delta w(n) \tag{10}$$

Similarly, data were grouped into various percentages for training, validation and testing with the initial group having the largest share for proper identification of patterns in weed classification.

Consequently, data were also normalised and regularized by subjecting to input transformation of a mean and standard deviation close to zero and one respectively. The essence of this is to reduce the impact or effect of previous layer on the future layers. The main motive of the adoption of this technique is the accurate prediction of weeds so that necessary actions will be taking on it to prevent harmful effects that may be associated with it.

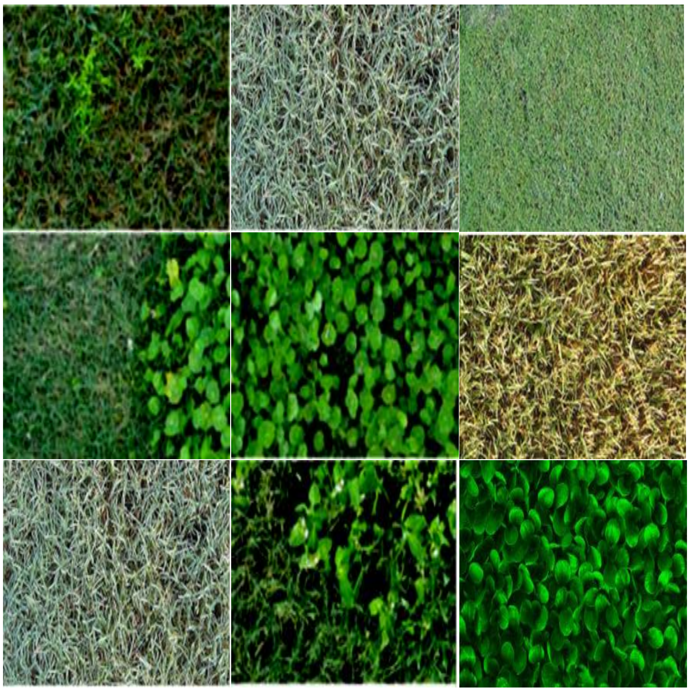

Fig.8. Collected weed samples for training the model

4. PERFORMANCE ANALYSIS AND EVALUATION

The performance metrics of each applied model for weed classification and detection is presented in this section. Precision is first calculated to determine how well the system does correctly what it is been instructed to do. Precision measure is calculated and a recall for its effectiveness is determined as represented in Eq.(11) and Eq.(12) respectively.

$$\text{Precision } (P) = TP/(TP+FP) \tag{11}$$

$$Recall\ (R) = TP/(TP+FN) \tag{12}$$

where

True Positive (TP): Weed detected by the system

False Negative (FN): Weed not detected by the system

False Positive (FP): Crop detected by the system

True Negative (TN): Crop not detected by the system

Derivation of higher values from both equations is a confirmation of the effectiveness of the system and adopted method for the identification of weed.

Implementation results performed with MATLAB, TensorFlow, Open CV, Keras, RGB weed detection database, GoogleNet, DetectNet, GoogLeNet and VGGNet are also presented. The adoption of Convolution Neural Network (CNN) accompanied by two maxpooling layers and twenty (20) epochs yielded a detection accuracy of ninety- five percent (95%). Similarly, a Support Vector Machine (SVM) classification adopted for the detection of weed also yielded ninety- five percent (95%). In addition, a chemical manufacturing company in Germany which specialises in the production of herbicides adopted robots for weed detection with the inclusion of AI techniques recorded an appreciable value of ninety (90%) accurate detection of weeds on a large farmland within a very short period of time.

Combining the processing techniques of Convolution Neural Network (CNN) and Absolute Feature Corner Point (AFCP) algorithm on a very large data set yielded ninety point three percent (90.3%) accuracy grade. Also, a comparison of K-Nearest Neighbourhood (KNN) classifier and Fuzzy Real Time Classifier (FRTC) on a set of sugarcane field correctly classified and predicted weeds to a precision level of 96.4% and 91.9% respectively.

Furthermore, computational accuracy of Artificial Network (ANN) and Scatter Transformation Technique (STT) in different given samples of weed research gave higher percentages of 92.5% and 85% respectively.

5. CONCLUSION AND FUTURE WORK

In this paper, the role of AI has been properly channeled towards weed detection. The methods and procedures employed in existing systems for weed detection have been clearly analyzed with a view of broadening conceptual knowledge towards improving and adopting more techno-efficient ways to detect weed on farm land. Weeds generally have a negative and damaging effect on crops, which on the long run may result in the farmer incurring great financial loss if not handled efficiently.

The application of Artificial intelligence in developed systems has not only been seen as a positive and welcome development but also a new and trending innovation with great prospects in agriculture and other areas of human life.

Thus, it is further concluded in this paper that AI will continue to play significant roles in weed detection and Agriculture in general, if human effort are consciously channelled towards developing, improving and adopting better techniques for developing techno-efficient intelligent systems to aid in agricultural related activities.

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