DEVELOPING INTELLIGENT WEED COMPUTER VISION SYSTEM FOR LOW-LAND RICE PRECISION FARMING

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ABSTRACT

Weeds infestation is one of the major problems facing rice production in Africa. Losses of rice caused by weeds yearly have been estimated at 2.2 million tons in Sub-Saharan Africa, the losses which are estimated at $1.45 billion. Weeds reduce the economic value of rice by causing an increase in the cost of production. Concerns have been raised on the health implication of herbicides, weeds seed in food crop and their effect on the environment, therefore, leading to the need for site-specific means of herbicide application to target only the weeds and ensure minimal seed contamination. This paper addresses these problems by the use Faster Regions with Convolution Neural Network (faster R-CNN) and Fuzzy Logic Controller (FLC) to develop an intelligent weed recognition system for better yield and return of investment in rice production in Sub-Saharan Africa. Faster R-CNN is a type of Artificial Neural Network (ANN) which uses convolutional features to map obtained features from an input image in order to identify the region of interest from the bounding box drawn around the weed image. As of the time of this research, the faster R-CNN method provides a faster means for real-time recognition as compared to other methods of ANN. The result of the recognition will be fed into the FLC to control the volume and time of spraying of the herbicides in low-land rice precision farming. The successful development and pilot testing of the anticipated intelligent computer vision system for rice weed control is expected to provide a faster and more efficient means of weed management for low-land precision farming for better food security in Sub-Saharan Africa.

KEYWORDS: *Weed, Site-specific, Artificial neural network, Deep learning, Faster R-CNN, Fuzzy logic control, Food Security*

INTRODUCTION

Rice (*Oryza sativa*), a plant species, is a seed of grass species grown as an annual plant. Rice is one of the world's three leading food crops and provides twenty per cent of the calories consumed worldwide by humans. It is one of the most consumed staple food among Africans and Asians, far more than half of the population of the world(Maclean, Hardy, & Hettel, 2013). Rice is an important staple food consumed by Nigerians. Rice is farmed in about 1.7 million hectares of the estimated 4.6 million to 4.9 million hectares' potential land for its production. The production environment for rice in Nigeria is the rain-fed lowland, rain-fed upland, irrigated lowland, deep water/floating and mangrove swamp (Nwilene et al., 2008).

There is three important periods of rice growth. The first is the vegetative phase in which foundation is laid and most farm operations are accomplished. The second is the reproductive phase which deals with building up stores, the panicles of the rice and the leaves develop to flowers. The third stage is the maturity phase when the flowers are fully matured and rice is ready for harvest. The difference in all the rice varieties of the world is the vegetative phase as the other two phases reproduction and maturity are fixed (Warda, 2015). There are different constraints which affect rice productivity such as weed infestation, poor extension system, low yield, poor milling, and poor drainage (Nwilene *et al*., 2008).

Weed is any plant that grows in an unwanted place. Akobundu *et al.* (2016) suggested that human disturbance of natural way of vegetation to meet recreational and agricultural activities led to the idea of weed. Civility and increase in knowledge of the nature of weeds have led to the identification, study and seeking of ways to control this notorious crop pest. No one weed is known by same local name so the botanical name was adopted to describe leaf form. The weed does not only affect yield but also affects the farmers by proportionate decrease and low return on investment in rice production, if not properly managed.

Weeds in rice plantation reduce the yield and quality of rice production by competing with the rice crop for nutrients, light and moisture needed for growth. Weeds, when not properly managed can cause an increase in harvesting, drying and cleaning costs. It can also lead to contamination of the seedling, therefore, undermining the profit which ought to be made on the rice (Odero and Rainbolt, 2011). To wrestle with this menace there is a need for these weeds to be identified, studied and control mechanism applied to them.

There is a need to remove the weed with minimum damage to the crop. Hand weeding is laborious and costly (Hansson and Ascard, 2002). The cost of labourers for a large farm takes a toll on the farmer. Labour shortages, illiteracy, ignorance, inputs and credits are major constraints for African farmers (Rodenburg and Johnson, 2009). Herbicides usage is one of the main ways which is adapted to weeds aside manual weeding. Celen *et al*. (2008) suggested that excessive use of these chemicals to control weed can cause environmental contamination which could lead to losses at harvest. Accurate information is needed to effectively remove or treat weeds in rice plantation. Precision farming (PF) is considered the best practical approach to achieve sustainable agriculture (Amin *et al*., 2011). The necessity to meet the demand of the current population of the country at the least cost and having a high output for rice is the main focus of this paper's precision agricultural approach.

Computer vision is a branch of artificial intelligence based on the theory of machine learning, image processing and pattern recognition. It involves equipping the computer with cognitive ability to acquire, process, analyse, understand digital image acquired through cameras, extract features from it and make valid decisions based on the acquired images. Images acquired are enhanced, segmented and features extracted from the images are classified using classifiers such as Artificial neural networks, servo vector machine or clustering methods (Rafael and Gonzalez, 2002).

Artificial Neural Network (ANN) is inspired by biological neural systems and learns over time based on prescribed data-set using processes like geospatial, multispectral techniques, and image processing techniques. While defining computing functions and distribution, the ANN sets out to look for the cost-effective and ideal way of arriving at a solution to a task (Technopedia, 2018). The Fuzzy Logic Controller is a type of fuzzy logic control based on verifiable observation of conventional statements of the system under control instead of quantitative terms. The relationship between input and output of the system under control is monitored by fuzzy logic. Fuzzy logic allows the emulation of human response and applies best-fit intelligence to the control data (Omega, 2018). It is applied in this study due to its inherent robustness to make the right decision in a precise scenario and its adaptability to changes in the environment like the presence of weed in rice farm production.

This research seeks to combine ANN, precisely Faster Regions with Convolution Neural Network (faster R-CNN), as a classifier and Fuzzy Logic Controller to develop an intelligent computer vision system, precisely, weed recognition and control system for managing weed infestation in low-land rice precision farming. The rest of this paper is organized as follows. Section II presents a review of related fundamental concepts and works, Section III discusses the proposed methodology, while Section IV concludes and opens the next directions of the research.

LITERATURE REVIEW

This section reviews the different methods that have been adopted for weed recognition and control by researchers in literature.

RICE DISTRIBUTION IN NIGERIA

Rice is a seed of grass species *Oryza sativa or Oryza glaberrima*. Rice is the third highest worldwide produced after sugar cane and maize and the world's second most important cereal crop after maize (AgroNigeria, 2014a). Rice provides 20% of the calories consumed worldwide by a human. Rice is monocot which is grown as an annual plant. About 480.3 million tons of rice is produced yearly, with

China being the largest producer in the world with a production of 206.51 million tons yearly (Statista, 2017). Nigerian rice is grown on 1.77 million hectares of lands. Rated on a social scale, rice can be ranked first because it is a global staple of most urban and rural area homes. Rice can be grown in every ecological zone, thereby making Nigeria great potential for its production (Ajala and Gana, 2015). Rice production has been relatively low in Nigeria due to ever-increasing the cost of fertilizers, tractor use, insecticides, manual labour, herbicides, transportation of produce and manual labour (Ajala and Gana, 2015).

There are six ecological growing environments for rice which is shown in Table 1. These growing environments are upland, hydromorphic, rain fed lowland, irrigated low land, deep inland water and mangrove swamp (Rodenburg *et al*., 2011). Figure 1 shows the characteristics of the rice-growing environment in Nigerian and Agro-ecological zones.

Table 1: Summary of the rice-growing environment (Longtau, 2003).

Type	Characteristics	Geographical spread
Upland	Rain-fed rice grown on free-draining fertile soils. This is also called dry uplands.	Widespread, except coasts, high rain forests and Sahel.
Hydromorphic	Rain-fed rice grown on soils with shallow ground water table or an impermeable layer. This is also called wet uplands.	Very widespread at the fringes of streams and intermediate zone between upland and swamps of rivers in the Savannah.
Lowland	Rain-fed or irrigated rice in aquatic conditions or medium groundwater table. Water covers the soil completely at some stage during the cropping season. These are called shallow swamps or fadama	Very widespread from high rain forest to the the Sahel.
Deep Inland Water	Rain-fed rice grown on soils with deep water tables. The rice crop floats at some stage and harvesting may be done from a canoe. These are also called deep fadamas or flood plains	Found in the Sokoto-Rima Basin and Chad Basin, floodplains of the Niger, Benue, Kaduna, Gbako, Hadejia and Komadugu-Yobe.
Mangrove Swamps	Rice is grown at the coast or swamps of the high rain forest.	Coastal areas and Warri area in Delta state.

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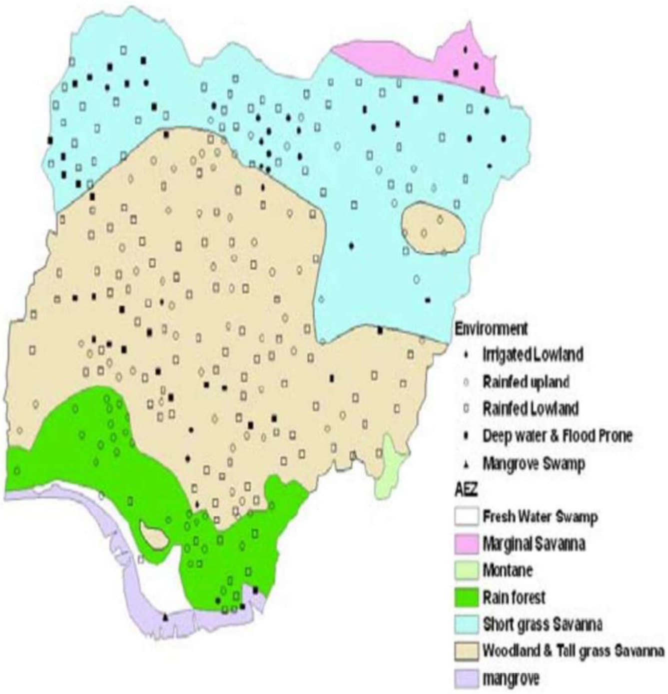


Figure 1: Map of Nigeria showing RGE and AEZ (Olaleye and Ogunkunle, 2009)

WEED MANAGEMENT TECHNIQUES

Various techniques have been reported in literature for managing weeds as shown in Figure 2. The available techniques can be grouped into:

i. Manual Techniques
ii. Semi-Automated Technique
iii. Automated Technique

Manual Technique

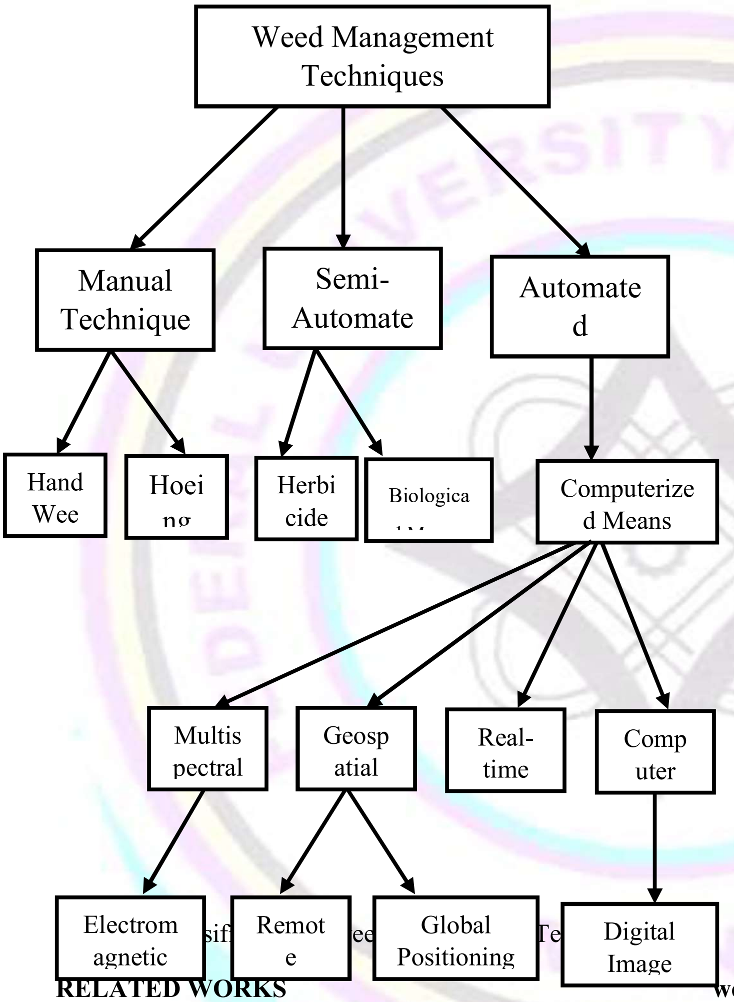
This technique consists of physical control that is ecologically friendly. It involves the use of hand or hoes to manually remove weeds from rice farms. The technique also includes cultural methods which involve proper seedbed preparation, mulching, maintaining clean reapers and tools, planting good quality seeds, planting varieties that suit growing condition, fire clearance, early flooding, bush fallowing and shifting cultivation or combination of these methods (Odero and Rainbolt, 2011).

Semi-Automated Technique

This technique consists of herbicide application and biological means of weed management. Though the Chemical method dominates this process, it involves the use of herbicides as another alternative to the cultural method in manual techniques (AgroNigeria, 2014b; Matloob *et al*., 2014). Examples of herbicides used are Butachlor, Propanil, Tamarice TMPL, Ronstar TMPL and Risane as stated by IRRI. IRRI suggested that some of these herbicides be applied to farm 2-3 weeks after transplanting the rice while others applied as post-herbicide control. The type of herbicides applied depends on either it is pre-planting (before planting), pre-emergent (before weed come up in plants) or post-emergence (after weeds have grown with rice).

Automated Technique

This technique consists of the use of computerized means to identify and control weeds on farmlands. The method involves, gathering information about the farms, storing the information, extracting features from them and then using the extracted features to make spraying decisions on the farmland. The devices from this approach can be mounted on tractors, drones or mini robots which are used on the farmland for weed control. These devices can be used inter-rows or intra-rows on the farmland. Automated method uses knowledge from machine vision based on digital image processing techniques, real-time differential spraying, which uses near-infrared channels (Feyaerts and Van Gool, 2001; Gerhards and Oebel, 2006); geospatial and information technologies based on remote sensing and global positioning systems (Ch ristensen, 2006), normalization vegetation index from near infrared, use of colour indices (Ribeiro *et al*., 2005), visible spectrum image processing, broad-spectrum image processing and other methods of site-specific spraying based on use of optical sensors, such as detect spray (Felton and McCloy, 1992), and Spray vision (Felton, 1995) among others.



RELATED WORKS

Tian (2000) proposed a method based on machine vision to recognise tomatoes seedlings from weed using environmental adaptive segmentation technique and knowledge-based vision system. Even though the system was able to accurately identify 65% to 78% of the target crops and wrongly identify 5% of the weeds, it provides no means of control for the weeds identified. Similarly, Yang (2000) proposed a method based on back propagation **Artificial Neutral network (ANN) model using colour indices features to distinguish young corn plants from weeds. The system was able to successfully recognize 80% of the weeds but it does not provide the method for t**he weed removal. Tellaeche *et al*. (2008) developed a vision-based method for weed identification based on Bayesian decision theory. The authors used a computer vision approach to detect and differentially spray weeds in the cornfield. The system used two main strategic processes; image segmentation and decision making based on Bayesian framework. Though the system was implemented on a tractor that does the differential spraying it does not provide means of continuous learning on the farmland.

Similarly, Odero and Rainbolt, (2011) used a well-prepared seedbed and cultural method to manage weeds in rice. By majorly using early flood, the system was able to suppress some non-aquatic weeds leaving the aquatic weeds to survive. The non-selective spraying of the farm can lead to herbicide wastage and incur more production cost. Also, Griepentrog *et al*. (2006) designed an autonomous intra row weeder for weed control based on GPS. The system simulated in MATLAB® has an accuracy of 80% and the field operation has an accuracy of 88% in weed removal. The system which was designed for upland with well-spaced crops to prevent damage from rotor blade which will not be applicable to low-land Rice farming. Pusphavalli and Chandraleka, (2016) proposed a robotic system that classifies weeds based on visual texture. The system uses knives for removing the weeds and this can damage the plant. The system consumes a lot of power and the weeds can regrow since they are not uprooted.

It is also imperative to review literature that works to reduce herbicide usage. Some of these methods that are based on site-specific spraying of weed infested areas include methods like detecting spray (Felton and McCloy, 1992), and spray vision(Felton, 1995) among others. These methods are based on optical sensors to reduce herbicide use by using reflectance to distinguish plants from the soil but these system does not differentiate between weeds and crops. Bossu *et al*. (2007) proposed a precision sprayer based on machine vision to distinguish weeds from plants using blob detection and Garbor filter but does not detect weeds in between rows. There are also other existing methods that detect weeds in wheat, soya beans and maize with less accuracy in real life field application.

Based on the problems identified in the reviewed papers, which are inability to tackle aquatic weeds, high power consumption, herbicides wastage, non-removal method and inability to learn on the farmland, this paper proposes an intelligent weed recognition and control system for low-land precision rice farming using a faster R-CNN for real-time recognition of weeds and FLC for spraying decision making. The system identifies the weeds and applies the appropriate quantity of herbicide on the weeds.

METHODOLOGY

System Overview

Electronic components to be used for the development of the system are, raspberry pi3, Pi-Camera module, DC liquid pump, LEDs, buzzer, 2-way relay module, Switch button and the power supply. The camera module, push a button and power supply shall act as input to the microcontroller (Raspberry pi3) while the buzzer and liquid DC pump act as the output. After the data set has been obtained and the features of images of the weeds have been extracted for recognition, a Faster region with convolution neural network algorithm, a type of artificial neural network, which is a form of the deep neural network will be used for training the dataset. The trained network is stored within the programmed Raspberry pi3. The designed system which will be attached to a knapsack sprayer. The camera to be attached to the other components will be attached to the body of the knapsack. When the switch button is pushed to start the system, the system starts taking a real-time image of the farmland and discards them as soon as it discovers it is not a weed. Once the camera sees a weed it will draw a bounding box around it and signal the farmer via a buzzer to allow him to wait for spraying. The raspberry sends message to the pump, the message consists of the quantity of herbicide to spray and the time for the spraying based on a fuzzy logic calculation derived from the input of the size of the bounding box and the faster R-CNN calculation. The proposed architecture of the system and block diagram is shown in Figure 3 and Figure 4.

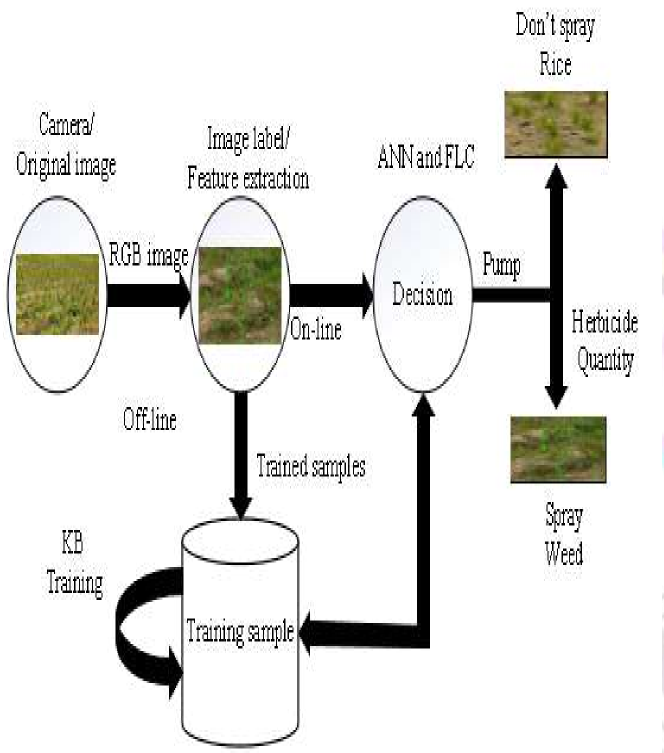


Figure 3: The Proposed architecture of intelligent weed recognition and control system

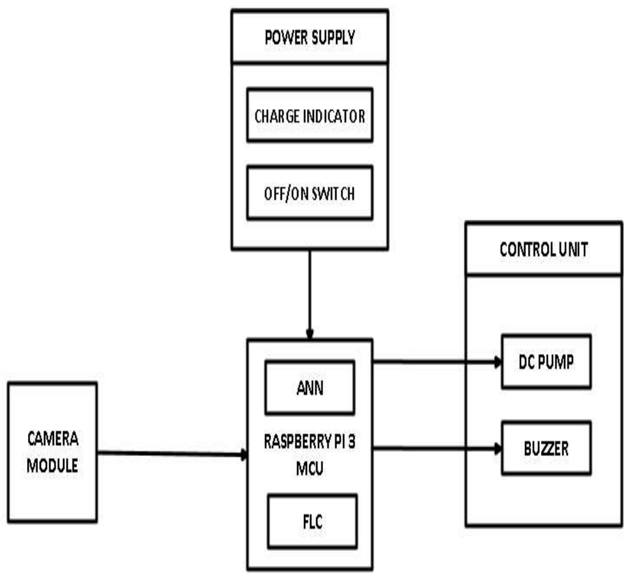


Figure 4: Block diagram of intelligent weed recognition and control system

Image acquisition system

Images of sixteen (16) different most common weeds of low-land rice were acquired from Google server and from the FUT Minna rice farm. Using the fatkum image downloader, an add-on on Google chrome browser to download image batches from Google server. The images obtained were carefully scanned and any non-weed images were deleted from the ones downloaded. Two hundred images of rice with weed was taken from FUT Minna Farm. Figure 4 shows an image of a FUT Minna rice farm with weed. The images from the school farm were taken with a 13 Megapixel tecno camon cx air camera with a resolution of 4160 X 3120 pixel with focus of 0.15 seconds.

Figure 4: Weed infested rice plantation obtained from Teaching and Research Field, FUT, Minna 18/05/2018.

Data Preparation

This is the process of putting the data into a suitable form which makes it easier for the data to be used. This process is important so that the images can be in a suitable format which can be used as a data set to train an artificial neural network for image recognition. The images of weeds obtained from Google server were resized to the same size of 250 by 250 pixels to reduce the size, using Adobe Photoshop. A tool for data preparation called label image (Labelling) was used to draw a rectangular bounding box around the weeds in the image and was labelled as a weed. The process is shown in Figure 5. The labelled image was saved in XML file format as a dataset for the training. A separate rectangular bounding box was drawn on the rice and labelled as rice, as many rice plants sighted in the image was labelled. The labelled image was saved in XML format as a dataset for rice.

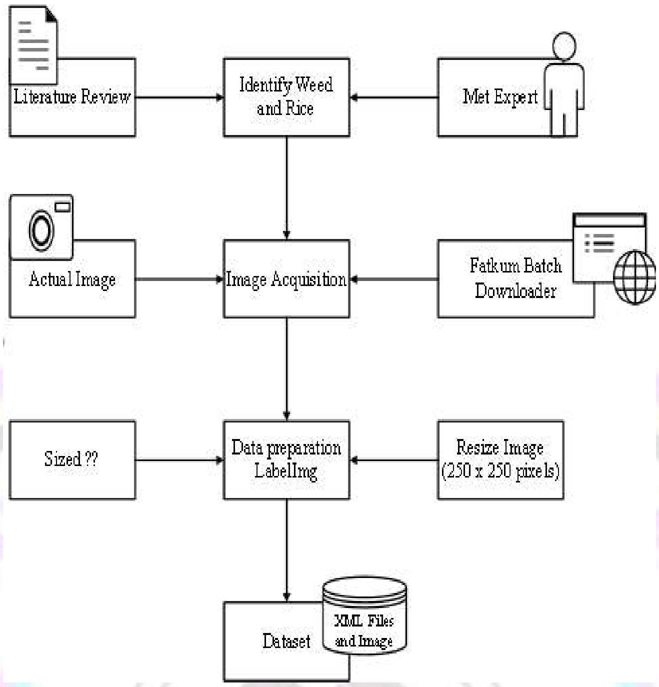


Figure 5: Dataset acquisition

Training the Intelligent Weed Recognition m

Model

An online Graphics Processing Unit (GPU) (Paper Space) was obtained for training the model. In training the dataset, eighty per cent would be used for the training, ten per cent for testing and ten per cent for validation. Paper Space is an online platform that gives limitless computing power in the cloud. The platform is used for deep learning, data exploration and gaming. GPU's are necessary for training deep learning models because they require a lot of computational power to run on, considerable hardware to run efficiently (Jenny, 2018). A deep neural network is an algorithm, the algorithm flow for training for creating a model for recognition is shown in Figure 6.

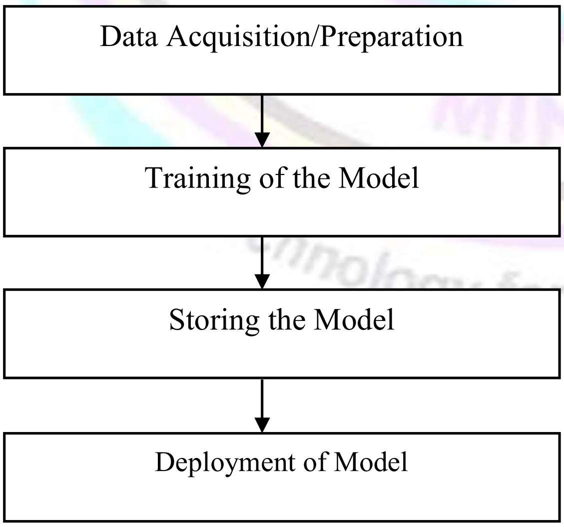


Figure 6: Weed recognition model using deep learning.

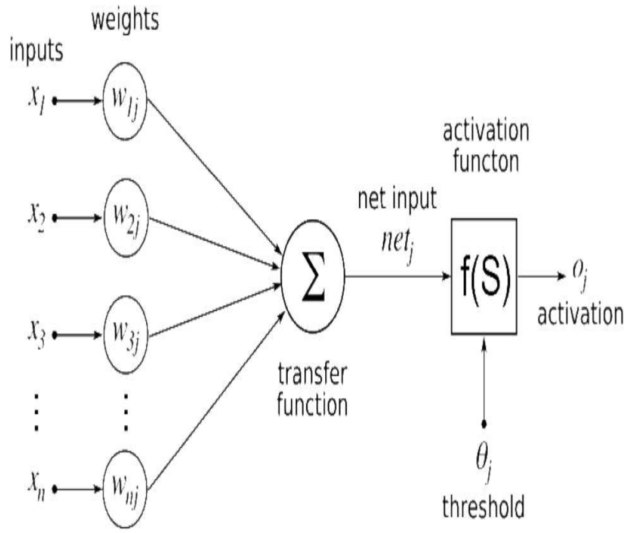


Figure 7: Typical Neural Network process (Shaikh, 2017).

In the algorithm training, two basic operations are performed, the forward and backward pass operations. Weights of the neural network are updated on the basis of the error obtained in the forward pass as shown in Figure 7. These operations are matrix multiplications. For a typical convolution neural network of 16 hidden layers. It has about 140 million parameters which are the weights and bias. Thinking of the number of multiplication applications, it would take typical system years to completely train the model (Shaikh, 2017). Thus, using the GPU can enable the model to be trained at once.

Electronic Circuit diagram of the system

Figure 8 shows the circuit diagram of the proposed intelligent system. In the circuit, the 15V direct current from the step-down transformer is passed through the bridge rectifier and regulated to 12v by the 7812-voltage regulator, the 12v is used for charging the battery which acts as a power source to the entire system. A transistor is connected across the 12v and 2k resistors connected across to act as a voltage divider. The charge and voltage control are used to enable the raspberry controller to stop charging once the battery is full.

Once the switch is pressed to connect the circuit, 7805 voltage-regulator is used to step the voltage down from 12v to 5v to power the other components (raspberry, camera, buzzer etc.) aside from the pump that taps voltage directly from the battery. The camera supplies real-time images which will be used for decision making by the raspberry pi. Once the weed has sighted the buzzer which is connected to the raspberry via a transistor and a resistor will alert the farmer to stop for spraying. The pump control connected to the raspberry then sends information to the pump which contains permission to spray and the time of spraying based on the size of the bounding box and the Faster R-CNN calculations. The pump module comprises a brushless DC 12V pump, relay, diode to prevent flash back and a transistor to act as a switch to the pump.

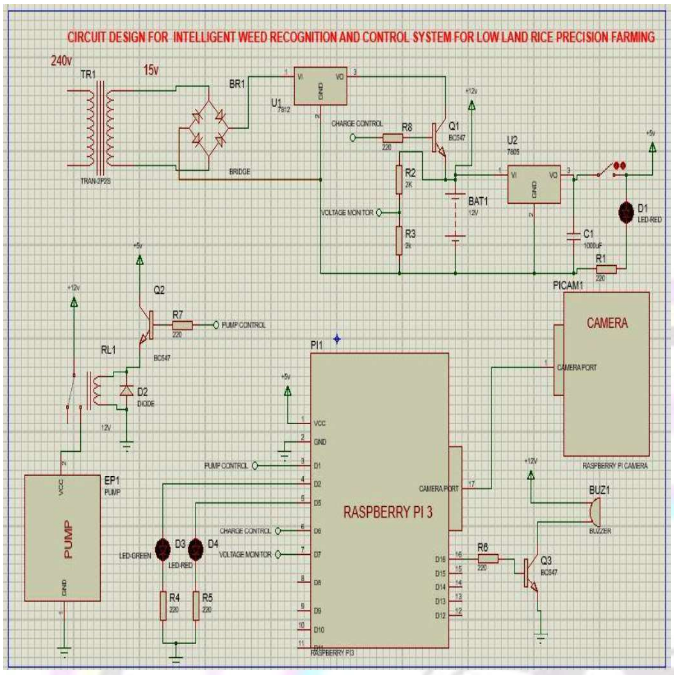


Figure 3.4 Electronic Circuit diagram of the anticipated intelligent system

CONCLUSION AND RESEARCH DIRECTIONS

In this paper, a critical study of rice distribution in Nigeria, various weed management techniques in literature has been studied. Similarly, papers have been reviewed on computer vision, precision farming. Consequently, weed data has been acquired and prepared for the training of the intelligent computer vision system for rice weed control. The effort is in progress to train acquired weed dataset image on paper space with Google Tensor Flow library using the faster region for convolution neural network, using python3 programming language and opencv2. The trained algorithm and corresponding programming code will be deployed in the raspberry terminal. After the recognition has been achieved with the picamera. The pump will be programmed with raspberry pi to give spraying with the recognized weed. Rigorous qualitative pilot testing shall be carried out at the Teaching and Research Field, FUT, Minna to determine the effectiveness of the anticipated computer vision system to address salient weed infestation rice production to enhance its yield. At this stage, the research is open to criticisms and recommendations.

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