A Brief Study on Paddy Applications with Image Processing and Proposed Architecture

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***Abstract*—Agriculture industry is one of the main economic activities in Asean countries. The activities involved a lot of crop planting and yield production in paddy, rubber, oil palm and so forth. Meanwhile in Malaysia, paddy is the third most widely planted crop after oil palm and rubber. Rice, produced by paddy, is considered to be one of Malaysia and Asean staple food and cereal crops. Due to its importance, there are a lot of efforts to ensure its safety, by having crop management of paddy plants such as, disease early detection system. The conventional way to detect plant defects is through human vision and it requires deep knowledge and understanding of the plant. The knowledge is gained through years of experience and observation. Therefore, the intelligent methods in this research are expected to assist the farmers in identifying leaf diseases. In this paper, we present the studies that deployed image processing technologies in paddy domain. Subsequently, we propose the architecture of our system for identifying the early stage of the leaf diseases and finding the weed species. The proposed system is expected to reduce the risk of diseases from becoming worse which may minimize the paddy yields.**

***Index Terms*—Agriculture, Image Processing, Leaf, Paddy Diseases, Weed, Supervised Method.**

I. Introduction

Malaysia has developed its economy through agriculture from many years back. The Malaysia Government programs have encouraged many research and technology development including data processing and analytics. Entry point projects (EPPs) for example, is to be executed in many sectors including universities. One of the EPPs main projects is to collaborate with the Ministry of Agriculture in order to enrich the agriculture information and communications technology. The purpose of this research is to apply Artificial Intelligence (AI) methods, namely neural network and fuzzy algorithms, in developing an intelligent recognition system for agriculture. Most of the current tasks in agriculture are still depending on the manual method. For example, the traditional ways to detect crop defects is still performed through human vision.

Technically, one requires deep knowledge and understanding of crop defects in order to identify the type of defect that infects the plant, but this method could be troublesome as it requires a lot of energy and patience. If the farmers fail to detect the plant defects while it is still in its early stages this could result in loss of yields or quality of crops. An integration of computer vision and AI technique would help to detect the plant defect in real time. The expected system would be able to connect the information and provides solutions on how to manage the defects. Thus, farmers are able to produce more and healthier yield of production for Malaysian folks. This research will adopt an appropriate method of AI so that, the delivered information will be more precise. In the future, the result of this research will be significant in providing information from planting the crops till processing the final products. This paper elaborates the related studies in Section II. Subsequently, the proposed architecture is described in Section III and finally, the conclusion is presented in Section IV.

II. Related Studies

The development of expert systems and agricultural information systems has been started years back since 1970s and progressing until now. The early application and information systems were mostly providing information and implementing rules or fuzzy rules for decision making [1]. Nowadays, most systems accept unstructured data such as, spatial data, images and so forth. The elaboration of related studies is divided into three subtopics, which include paddy applications, image capturing methods and image processing methods that can be implemented and suitable in paddy applications. The purpose of the application could be various. We analyzed the literatures and we conceptualized the existing application into three main purposes.

A. Identification of Paddy Fields

Qulin and colleagues [2] makes use of Radarsat's Syntethic Aperture Radar (SAR) data for detecting the paddy fields by leveraging the edge detection and extraction. The edges were enhanced by 2D directional filtering algorithm before they were detected by using the non-linear operator to threshold the image. A research conducted by Hoang and colleagues [3] used polarimetric radar data from Radarsat-2 satellite and Support Vector Machine (SVM) for rice field classification. Then the thresholding method based on rice backscattering in Horizontal

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transmit-Horizontal receive (HH) polarization was applied to the data. The processed polarimetric data was classified by the SVM to identify rice field. Later, Ichikawi and the team [4] depend on RapidEye satellite to identify paddy fields. The images used was orthorectified, segmented and the combination of Red, Green, Blue (RGB) channels and Near Infrared (NIR) channel were used for generating normalized difference vegetation index (NDVI) and bimodal histogram from NDVI for each segment. The histogram served as the comparison of the types of fields which are paddy, other crop and uncultivated land. Table 1 shows the summary of the several existing paddy field detection systems.

TABLE I. PADDY FIELD DETECTION SYSTEMS

Author	Images	Related Methods
Qulin et al., 2004 [2]	Satellite	2D directional filtering algorithm
Hoang et al., 2011 [3]	Satellite	Thresholding method SVM
Ichikawa et al., 2014 [4]	Satellite	Histogram Analysis

B. Paddy Leaf Isolation and Detection

This section presents several researches done on paddy leaf. The develop application involves mainly distinguishing and extracting paddy plants and leaves from its surroundings. Tang has conducted research with a close-up leaf extraction from complicated background using Hue, Saturation and Intensity (HSI) colour channel, marker-controlled watershed segmentation, and solidifies measure for choosing best channel for extraction, albeit without using paddy as the subject [5] and they managed to differentiate between targeted leaf and the complicated background which includes soil, interference, and overlap of non-targeted leaves.

Next, Ponti [6] tried in isolating crops from other elements in aerial images. The research uses a low cost remote sensing device (Helium gas balloon) for capturing the bean crop field and vegetation indices to improve the contrast and visualization of the vegetation. After that, the image is processed with mean-shift filter, converted into a binary image using Otsu's method and the original method was segmented based on the binary image. Another research, which has been done by Nguyen and team [7] by utilizing Genetic Programming (GP) in order to detect rice leaf from rice field images. A classifier program using genetic programming was evolving it with 20x20 pixels of various parts of rice plant images, both positive (Leaf parts) and negative (Non-leaf parts). Table II shows the brief description on paddy leaf applications.

TABLE II. PADDY LEAF APPLICATIONS

Author	Images	Related Methods
Tang et al., 2009 [5]	Close up images	Hue, Saturation and Intensity (HSI) colour channel, marker-controlled watershed segmentation
Ponti, 2013 [6]	Aerial (remote sensing)	Mean-shift filter, converted into binary image using Otsu's method
Nguyen et al., 2013 [7]	VGA camera	Genetic Programming (GP) classifier

C. Paddy Disease Detection and Nitrogen Level

Kurniawati, Abdullah, Abdullah and Abdullah [8] extracted the lesion type (Using thresholding based on local entropy and Otsu's method), boundary colour, spot colour and damaged leaf colour. The features will be processed by production rules based of experts' knowledge with forward-chaining method in determining the type of diseases. Meanwhile, Orillo, Cruz, Agapito, Satimbre, and Valenzuela [9] also extracted features of the leaf, including segments of disease, mean of RGB channel, standard deviation of RGB channel and mean of HSV channel and these features were evaluated by Backpropagation Neural Network (BPNN) to determine the type of the disease. Later, [10] also developed BPNN to detect type of paddy leaf diseases using the RGB and fuzzy rules extraction.

Other than diseases, the amount of nitrogen in of paddy leaf is also important in order to determine their health. Orillo, Emperador, Gasgonia, Parpan, and Yang [11] used close-up images of paddy leaf and all features were processed by BPNN to detect the colour level based on Leaf Colour Chart (LCC) and manage to get the accuracy of 93.33%. The comparison is done between leaves' colour of segmented sections of paddy field and Leaf Colour Chart (LCC). Other research conducted [12] using pictures taken from UAV and with lens correction technique they managed to get the weighted accuracy of 95.04%. Discussed researchers above are shown in Table III.

TABLE III. RELATED APPLICATIONS

Author	Images	Related Methods
Kurniawati et al., 2009 [8]	Close up images	Thresholding based on local entropy and Otsu's method Rule based system
Orillo et al., 2014 [9]	Close up images	RGB and HSV BPNN
Adzhar et al., 2015 [10]	Close up images	BPNN
Orillo et al., 2014 [11]	Close up images	BPNN
Aidil et al., 2015 [12]	UAV	HSV and BPNN

D. Paddy Grain Classification

Some researchers also investigate on the possibility to differentiate between paddy types through their grains as shown in Table IV. The research would focus on grade quality, evaluated the exterior quality of the grain, which are head rice rate, chalkiness, and crackles [13]. By improving the grey images of the grain using Three-sect Linear Transformation method, the chalkiness is greatly enhanced and easily extracted based on chalk's grey pixel value range. The crackles were detected based on the difference curve generated from grey exponential difference where a grain's curve with trough shown that it was crackled. Another research proposed a classifier for the grade of the grain, whether it Premium, Grade 1, Grade 2 or Grade 3 [14]. This research applied Cooccurrence Matrix (GLCM) texture feature extractor and variance, means and RGB and HSV channels as the colour features of the grain images and BPNN as the classifier. Later, a team had been conducted on finding the automatic way to differentiate multiple type of grain, which are Xiannong, Jinyougui, You166, Xiannong, Medium You using images of the grains were segmented, and the features extracted were ratio of the sound area to the area of the whole section and ratio of the sound area to the area of embryo part and they were processed by BPNN classifier [15]. Other than that, a classifier system is developed and able to differentiate between regular rice and sticky rice based on unmilled grains exterior characteristics [16].

TABLE IV. APPLICATION FOR PADDY GRAINS

Author	Images	Related Methods
Yao et al. [13]	Grey grain images	Three-sect linear transformation Principle Component Analysis (PCA) and Regression Analysis
Pabamalie & Premaratne, 2010 [14]	Grain images	RGB and HSV BPNN
OuYang et al., 2010 [15]	Grain images	Segmentation, BPNN
Punthumast et al., 2012 [16]	Grain images	RGB histograms

E. Image Capturing and Preprocessing

Most of the paddy applications used either images from close up or aerial photography. The method used for capturing these images is aerial photography, which includes remote sensing and photogrammetry [17]. Remote sensing makes use of new technologies such as advances sensors, satellites and Unmanned Aerial Vehicle (UAV) to capture remote images, as shown in Fig. 1. Meanwhile, photogrammetry is the extension of aerial photography and remote sensing. It uses images captured from different angles of the same area to be processed for generating a three-dimensional map [18].

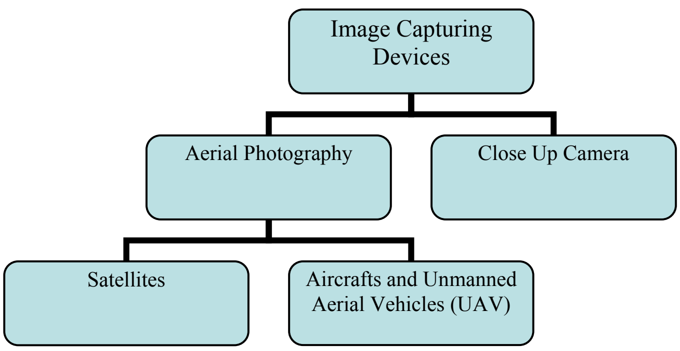


Fig. 1. Image Capturing Methods.

To enable all the methods of remote sensing and photogrammetry, to be carried out, specific devices which act as carriers for the imaging sensors must be used. The most commonly used carrier devices are airborne (Aircrafts and UAVs) and space-borne (Satellites). The main factor that will be evaluated in deciding on which device to use is the device' cost. According to DroneApps [19] and Brown [20], cost of launch and operation of popular Landsat 8 satellite was estimated to be around 855 million USD, Cessna 172 aircraft has cost around 300, 000 USD and UAV can be bought with the price around 100 to 13 million USD depending on the features and target users. To overcome the high price, some of organizations which own the devices provide image capturing services for masses at a low price per kilometre [19] . Other than price, the capabilities of each device also take into consideration. Satellites can capture images at meter level and cover a large part of the land. The drawbacks of satellites are the resolution of the captured images are not good for detailed observation, satellites can only revisit a place after three days and the image captured can be easily affected by bad weather .

Compared to satellites, UAVs can capture an area at very low level (centimetres) resulting in high resolution images which are suitable for detailed observation and they also can be deployed quickly to the targeted destination. Unfortunately, the drawbacks of UAVs, are they can only capture smaller scale of land per image resulting from limited flying height, their flight time is limited by their battery capacity and inclement weather may cause them to fly off the course [20, 21]. The best compromises in terms of capabilities are aircrafts. It is because aircrafts can capture images at higher resolution than satellites and capture large areas per image compared to UAVs. Paddy leaves and grains, most likely are captured using a digital camera in order to have more precise and close up images. However, the use of airborne devices or small drones could be necessary in order to cover more area and spaces of paddy fields.

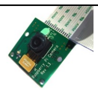
The initial stage of pre-process usually involves image combination. An image of an area is usually too large to be fit into a single image, especially for camera sensors attached to airborne devices. This is because airborne devices can only fly at low altitude when taking pictures which limits the coverage of the camera [22]. To overcome this, multiple shots will be taken across the area and the smaller images will be combined into one, single large image of an area. According to Zhang, Lin, Wen, Zhang, Liu, and Wang [22], one of the methods to combine these smaller images is through the use of an image mosaic together with phase-correlation method to detect matching region for combination. Other than that, Global Positioning System (GPS) and Inertial Navigation System (INS) also can be used for determining the location of each image along the path of flight [23]. The image also will be processed with other image pre-processing algorithm before its features can be extracted. The most common image pre-processing used is conversion of image from Red, Green, Blue (RGB) channels to Grayscale. This is required for some feature extraction algorithms that use grayscale level, such as Smallest Univalue Segment Assimilating Nucleus (SUSAN) and

Forstner [24, 25]. Other pre-processing methods such as contrast boost, noise removal and region isolation are also used to increase the chances of processing success [26].

III. Proposed Architecture

Based on previous research, we proposed the architecture for the paddy plant recognition system. The purpose of this system is to recognize paddy plants that were infected with diseases and later the farmer will be given steps in controlling the diseases. Without the system, farmers need to contact the expert from local research institute to inspect the paddy field and observe the symptoms. In the absence of the expert, an early screening can be performed as the system could recognize the type of disease and the farmer can take pre-caution actions prior to the arrival of the expert and able to control diseases at the early stage. As shown in Table V and Table VI, we simplify the architecture into two layers: the input layer for image capturing and the image preprocessing and learning engine for the screening of the paddy diseases.

TABLE V. Input Layer

Input Layer		
Activities	Devices or Components	
Image Processing • Size • Adjustment • Image Enhancement HSV method (Hue,Saturation,Value) • Image Segmentation	Digital Camera/Pi Camera	
	Raspberry Pi 2	
	Python OpenCV	

We include Weed Checker module in the architecture as paddy field might be threated by other wild plants. This module is proposed as many researchers also have developed the automatic weed detection. Weed detection has been developed by some other researchers in different plants, such as oil palm and corn. A group of researchers had built a system to detect broad and narrow weeds in oil palm plantation [27]. They used Gabor wavelet and Fast Fourier Transform (FFT) algorithm to obtain the feature vectors named difFFTgabor for each weeds images and SVM as the classifier. There is also another research that constructed a weed recognition system and integrated it with cultivator robot, however, the system is more on detecting crops in a corn field [28]. The system applied frequency filtering based on FFT2 and density filtering to distinguish between crops, weeds and background and they managed to obtain the accuracy of 92.8% for 80 samples. The flow of the core engine for learning the leaf features and classification is shown in Fig. 2. It involves the activities of development the prototype, evaluation and integration. Once the prototype is ready, the user, such as MARDI and farmers will be asked to get involved in improving the content and processes. We explained the experimental setup for paddy leave diseases only; while the weed checker module is still under reviewed and experiment.

TABLE VI. Learning Layer

Learning Layer		
Activities	Devices or Components	
	Paddy Leaf Diseases	
	Bacterial Leaf Blight	
Supervised method Training and testing Fuzziness Checking	Leaf Blast	
	Sheath Blast	
	Weed Checker	
	Echicochloa crus-galli	
	Ludwigia hyssopifolia	

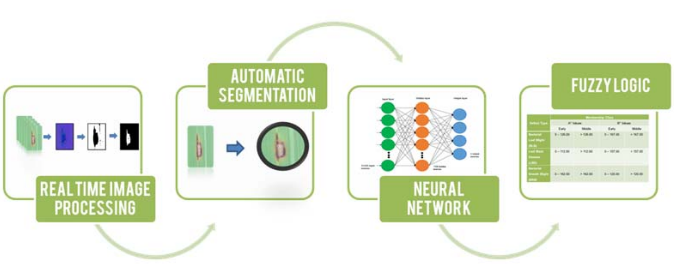


Fig. 2. Flow of the process of core engine.

IV. Experimental Setup For Paddy Leave Diseases

The images of paddy leaves with and without disease were obtained from MARDI research station in Bertam, Pulau Pinang. The images were captured using Canon 550D with two lenses, Canon 50 mm 1.8 F and also Canon 20-80 mm with 4 - 5.6 F lenses. Total images we had collected are 1207 leaves with diseases at different stages and 239 healthy leaves.

The core engine mainly has three stages; the first stage is the pre-processing and to perform auto segmentation of the images, next stage is to determine the type of diseases by applying the back-propagation neural network and finally the fourth stage is to recognize the stages of these diseases by using fuzzy logic[10].

A. Preprocessing and Segmentation

The preprocessing was done using MATLAB to read the RGB image. Since the images collected are not uniformed, the images have to be manually cropped and resized the cropped images into dimension of [50 X 50]. After that, the shape of the leaf is extracted by using morphological operations. The RGB images were converted to Grayscale color profile and then, the edges were defined by Canny Edge method. Later, the process of smoothing the images was done with combination of image dilation and erosion. This is done to enhance the image's features.

The colors in defect area in the images were processed in order to determine the stages of the disease. The resized images of RGB color were converted to LAB color images. A scatter plot was used to display the data of the LAB color. The images were later represented in the form of decimal numbers for both values of A* and B*. Further, a color descriptor is used to display the color of an image in a readable data form. At this stage, the diseases can be categorized to two stages; that is the early and middle stages using fuzzy rules [10].

B. Back-propagation neural network

We designed BPNN with three layers that is the input layer, hidden layer and the output layer. We identified 2500 nodes as the input layer, 1250 nodes for the hidden layer, and three nodes for the output layer which represent the type of paddy diseases (BLB, LBD and BSB). In BPNN, the training process is crucial in order to recognize the paddy disease. For this work, 28 images were allocated for BLB at its early stages, 28 images at its middle stages. For LBD there are 33 images in its early stages, and 43 images in its middle stages. Lastly, for BSB, there are 32 images allocated. The total number of images is 164. The ratio of data used in the system is 80:20 where the data for training will be 80% which is 133 and data for testing will be 20% which is 31 images. At this point of time, we able to reach the accuracy rate within 70 to 80 percent. We would later to investigate in processing the paddy leaves without manually cropping the images.

C. Conclusion

Rice is always becoming the main dish among Malaysian and also Asean population. However, the fact that Malaysia consumes more rice compared to the production. Therefore, it is crucial to take action in planting and producing sufficed paddy and to maintain the healthy plant. In order to supply knowledge through technology adoption, the proposed architecture of a system is designed to help paddy farmers in understanding the diseases and expertise to store the knowledge in the system. In terms of algorithms, the paddy plants and fields have their own technical problems in applying methods in image processing, such as lighting, background problems and also noises and learning algorithms, within or outside of the portable devices.

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