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Intelligent Based Image Processing Model for Ethiopian *Enset* Diseases Diagnosis

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Abstract: The downfall of agriculture is highly rampant in many developing countries such as Ethiopia, Pakistan, Bangladesh, Afghanistan, Eritrea, India and others. This is so a great focus in our country's strategic plan for contributing growth of economy. There are many issues to decline this potential field, viz. weather, shortage of rain, pollution and diseases. However, *Enset* crops in Ethiopia are attacked by numerous insect pests and diseases which have been one of the difficulties in the development of agricultural sector. To handle these problems, experienced farmers and domain experts should only use visual inspection for the diagnosis of such plant diseases in-place. This has defects due to lowering the accuracy rate when compare to soft computing approaches. This research dealt with an intelligent based image processing techniques for *Enset* disease diagnosis to examine the various *Enset* leaf diseases. In order to create the knowledge base system, a total of 570 sample *Enset* images for the three diseases including *Enset* bacterial wilt, *Enset* black sigatok and *Enset* panama wilt are employed and this real dataset was demonstrated using MatLab R2020b platform. In the first stage, the image of the *Enset* disease is subjected to image processing techniques. Particularly, the possibility distribution algorithm applied to enhance the contrast of inputted image, followed the Otsu method used to select region of interest and then features such as GLCM, color and shape are extracted. Next a comparative analysis was made using various machine learning algorithms to identify each class labels based on the trained patterns. The developed system can successfully identify the examined *Enset* diseases using ANN and Kernel RBF with an accuracy of 91.8% and 79.41% respectively.

Keywords: *Enset* Diseases, Possibility Distribution Algorithm, Otsu Method, Color, GLCM, Shape, Kernel-RBF, ANN

1. Introduction

Agricultural production has evolved into a complex business requiring the accumulation and integration of knowledge and information from many diverse sources. In order to remain competitive, the modern farmer often relies on agricultural specialists and advisors to provide information for decision making process. Unfortunately, agricultural specialist assistance is not available when the farmer needs it. In order to alleviate this problem, intelligent systems were identified as a powerful tool with extensive potential in agriculture [1].

Limited dissemination of created and innovated knowledge from the research centers to end users affects farmers' productivity. Whenever new knowledge is created from the research center, it is difficult to transfer the expert's knowledge to farmers and extension agents because this needs budget, high number of experts to train farmers and extension agents to share the knowledge created from the research center [2].

Over the last five decades, our country's researchers and domain experts have put much effort to generate improved agricultural production technologies and deliver it to the users. Even though these several conventional technologies have been developed, the agricultural research and innovation centers pursued in the past have not been very successful to deliver appropriate technologies to end users. Accordingly, the existing research approach and process was reviewed and found be lengthy and less effective to deliver appropriate technologies and unsatisfactory to the research customers [3].

Increasing the potential productivity both in terms of quantity and quality; a number of challenges are faced by farmers, agricultural specialists, expertise and others in our country. Farmers encounter major challenges that cause severe yield loss in Ethiopia while to misdiagnose the diseases that affecting their crops due to lack of knowledge.

Ethiopia is one of the grand producers of *Enset* in African continent countries. There are several issues and diseases which try to decline the yield with quality. Particularly, diagnosis of potential diseases on Ethiopian *Enset* is based on traditional ways and due to limited research attention given to *Enset* crop production. The visual observation of the experts is the main approach that commonly used for detection and identification of such plant diseases. As a matter of facts, visual or manual detections may have defects in terms of accuracy in detection along with lower precision.

Given the limited availability of resources and expertise on *Enset* pathology worldwide, the need for an automation system to classify and identify *Enset* diseases is urgent. In our country few researchers found the promising solutions to different plant diseases diagnosis such as maize [4], rose flower [5], coffee [6], *enset* [7] and others using computer vision and machine learning techniques. Motivated by advances in computer vision, especially artificial neural network (ANN) and Kernel Radial Basis Function (KRBF), which produce remarkable results in the field of image classification, the researcher proposed a new system based on comparisons of such algorithms for *Enset* plant disease diagnosis.

Designing and developing the computer based image processing and diagnosis system has been increasing the diagnosis system constantly in agricultural fields. If image processing and analysis can be applied to *Enset* diseases images in the number of areas, with very good potentials for future agricultural applications such as achieving automatic diagnosis. It is hoped that an intelligent and automated agricultural diagnosis and navigation can be carried out with a consistent level of performance with the aid of a computer. This could be possible with software that is capable of image analysis, such as identifying the region boundary and the region classification [8].

In developing countries like Ethiopia, it is expensive for a large farm to go to agricultural expertise for their *Enset* diseases problem. Every year a large number of *Enset* plantations in the developing countries suffer due to different types of *Enset* diseases. So, it is very necessary for both the infected *Enset* plant and expertise to have an automated *Enset* disease diagnosis system.

The rest of this study is organized as follows. Challenges of *enset* production are presented in Section 2. In Section 3, we discussed the architecture of proposed prototype. Experimental results are reported in Section 4. Finally, the conclusion and future works were presented in Section 5.

2. Challenges of *Enset* Production

As a matter of fact, the decline of *Enset* productivity was primarily associated with decline in soil fertility which is partly due to decreased number of animals to produce enough manure to support the *Enset* fields. As a consequence of the shift accompanied by increasing human population, in recent years, the *Enset* system has been in jeopardy in southern Ethiopia due to the desire of town dwellers to shift to the 'prestige' foods of cereals there by affecting the market opportunities to *Enset* products.

Several types of diseases are known to affect *Enset* plants under field conditions. So far a number of fungal, nematode, viral and bacterial diseases were reported to cause damage at different degrees of intensity that was mainly explored by Quimio research finding since 1992. The occurrence, distribution and the incidence level also indicated to vary from one *Enset*-growing locality to the other. Therefore, the damage inflicted by each disease also varied. Among various diseases, *Enset* bacterial wilt and Fusarium Wilt is considered as the most dangers one that reduces *Enset* yield [9-11].

According to scientific perception, in a more advanced stage of disease development, most of the leaves wilt, breaks at the petiole and wither. Eventually, the whole plant dies and rots to the ground [12]. The following list of points was presented the symptoms of bacterial wilt:

a) Wilting starts when pathogen densities increase throughout the plant, which prevents sufficient water from reaching the leaves due to vascular dysfunction.
b) High bacterial cell densities, plant produced tyloses and gums, and byproducts of plant cell wall degradation may be contributing factors.
c) EBW is a vascular disease that results in yellowing and wilting of leaves.

Figure 1. *Enset part was infected by Bacterial Wilt.*

Fungal foliar diseases attacking *Enset* are numerous and widespread, however, most are undescribed and unidentified. Usually this disease kills young plants while older transplants are severely stunted due to rotting of the roots. The most know type of fungal foliar disease is Fusarium wilt of *Enset*. This disease produces two types of external symptoms: "yellow leaf syndrome" and "green leaf syndrome [13].

Figure 2. *Enset part was infected by Fusarium Wilt.*

3. Architecture of Proposed Prototype

Development of this Prototype followed the fundamental process of image processing and analysis. Samples of affected *Enset* images were collected and grouped to each disease type by the experienced experts before the experiment. After applying the image analysis techniques by using the best algorithms on the well prepared datasets, then the necessary and major features of the *Enset* diseases were extracted and provided as input data for the classification component for the training purpose. The other independent datasets were used for testing. The color, shape and texture features were extracted and fed to the different classifiers of Kernel RBF and Artificial Neural Network.

In this work, disease identification was done by using characteristics of *Enset* plant. The features of normal and diseased *Enset* image features were extracted then these features were also trained and evaluated through kernel RBF's and ANN. As a result a defined *Enset* image feature repositories was created. Figure 2 shows the architecture of the proposed system.

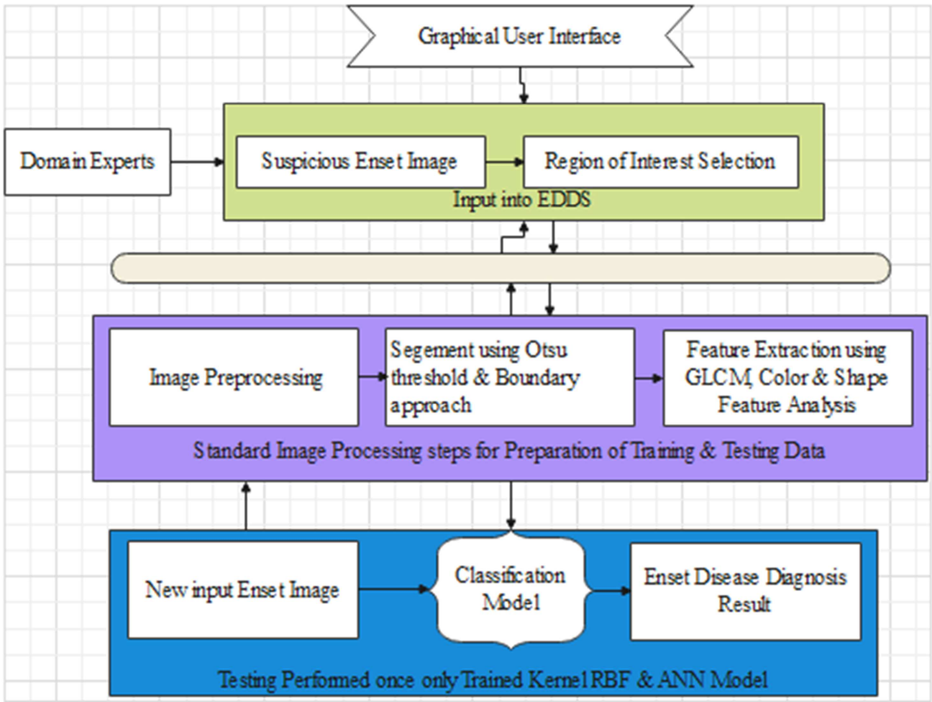

Figure 3. *Architecture of the Proposed Prototype.*

3.1. Image Acquisition

This was the first stage of every image analyses and computer vision. In this study *Enset* images were collected using smart camera devices based on its appropriate setup from Areka agricultural research center and some selected areas of Ethiopia.

3.2. Fuzzy Set Theory Based Image Enhancement

The main purpose of this step was to improve the quality of *Enset* image by removing unrelated and extra parts in the background of the image for further processing. Particularly the pre-processing techniques such as removing noises, adjusting the intensity or brightness, adding edge detectors were included for enhancing the detailed parts of *enset* leaf.

Due to different factors, the image we collected may not be cleared and improved. Good selection of pre-processing techniques could significantly improve the accuracy and reduce the computational time of the next image analysis processes. For this process, the contrast enhancement, color transformation and image scaling was applied. Typically, fuzzy set theory called possibility distribution algorithm was used to improve the quality of the contrast from the observed *Enset* images [14].

3.3. Otsu Based Image Segmentation

In this step, the model was separating the infected part of the enhanced *Enset* image from its background. The segmentation process changes the image into something that was more meaningful and easier to analyze.

3.4. Feature Extraction

In the proposed system selection of important features were necessary for classification which was a main problem and challenging issues.

3.4.1. Grey-Level Co-Occurrence Matrix

As we were using texture analysis for the classification of diseases, we have to extract the features first from the images. For that purpose, we have used the color co-occurrence methodology which is developed through the GLCM (Grey-level Co-occurrence Matrices). The gray level co-occurrence methodology is a statistical way to describe shape by statistically sampling the way certain gray levels occur in relation to other gray [15].

3.4.2. Shape Analysis and Measurement

The objective of image analysis was extraction of quantitative pattern information from.

The performance of any shape measurements depends on the quality of the original image and how well objects are preprocessed.

a) Object degradations such as small gaps, spurs, and noise can lead to poor measurement results, and ultimately to misclassifications.
b) Shape information is what location, orientation, remains once and size features of an object have been extracted.
c) Shape descriptors describe specific characteristics regarding the geometry of a particular feature. Shapes can be described by many aspects we call shape parameters such as Area, eccentricity, Euler number and Orientation.

3.4.3. RGB Color Moments and HSV Color Quantization

These features are the most critical object descriptors during image analysis. In the first step of this, the original RGB *Enset* image was inputted to the system and extracted the color features based on statistical variables. For measuring the number of bins of HSV color channels, first the RGB channel was mapped to this model and then the model computes the numbers of each bin value for this color. Generally, these features indicate the appropriate color results for the *Enset* disease diagnosis (EDD).

3.5. Training of Samples

At this phase, the affected images of the three *Enset* diseases were collected from the pre-planned sources and labeled under their diseases category. When these images were thoroughly complete the fundamental steps of image processing and analysis as described in the previous sections then for each classifiers the desired classification model was created after a given unit of time. This contains a targeted class label of *Enset* image patterns: the combination of texture, color and shape features of the respective image and their respective target class which were the primary inputs for any decision making process. Lastly, we used an appropriate model to identify *enset* diseases and clearly stated the number of inputs to the specified target class labels.

3.6. Diagnosis of Enset Leaf Diseases

After the extraction of all the necessary features, we have to compare them with our pre-calculated dataset stored in a ".mat" file. We have used the comparative analysis of Kernels SVM and ANN classifiers to classify the three *Enset* diseases such as *Enset* bacterial wilt (EBW), *Enset* black Sigatok (EBS) and *Enset* Panama wilt (EPW).

Kernels SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements [16]. The dominant approach for doing so is to reduce the single multiclass problem into multiple binary classification problems. In this case, the classification of new instances or input images for the one-versus-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class and detects the particular disease [17].

Another supervised learning approach called artificial neural network was used to diagnosis *Enset* diseases based on prior learned or trained model and classify the class labels for the recognized disease types. For computing such potential process the model must follow the general learning paradigm that takes selected features as input patterns and parallely process them with multiple weights, functions and biases then produce reliable results for the disease class.

Finally, the researcher made a comparative analysis of ANN and Kernel RBF to EDD system by measuring the accuracy of the proposed models using evaluation system called confusion matrix method.

4. Experiment

4.1. Dataset Partitioning

The images of the dataset were collected from different places of southern Ethiopia and *Enset* research centers. These images were collected by using a canon digital camera and some of them were collected from secondary sources. So, this experimental part was held in two phases and used a total of 570 various numbers of three *Enset* leaf diseases and one normal *Enset* were identified.

4.2. ANN Classification Model

In the first phase of simulation, five ANN classification model experiments (Experiment 1 (Exp1)…Experiment 5 (Exp5)) were practiced using the features of shape, color, texture, color and texture, and the combination of shape, color and texture.

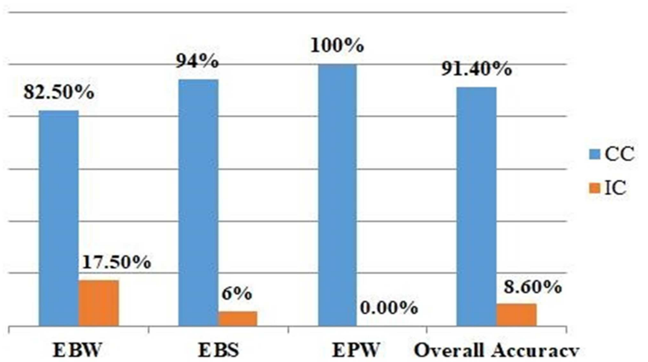

Figure 4. *Experimental Results of ANN Classification Using Texture, Color and Shape Features.*

These experiments were also applied for the most fit pattern recognition neural network architecture of the layers viz. 5, 7, 6, 10 and 13 hidden nodes respectively. The partitioned dataset was trained and tested to predict the three class label of *Enset* leaf images. And also the performance of the model was measured for each five features using confusion matrix; that indicates the correctly classified *Enset* leaf images and misclassified part of these from the sample dataset. In these experiments, Exp1 and Exp3 have shown slightly similar accuracy's for correctly classified images and in-accuracy for misclassified images. And also Exp4 and Exp5 have indicated nearly similar promising result to measure the given sample *Enset* dataset. Particularly, features like color and texture had significantly increases the performance of the model and also determined the *Enset* leaf images patterns when they used alone or combined each other. However, shape feature may affect the performance of model when it used alone. It may contribute a paramount of importance when combined to the color and shape feature as a whole rather than integration of them. However the symptoms of *Enset* plant diseases were most likely similar in nature, the combination of shape, color and texture features using ANN classification model gave an excellent promising result of 91.4% accuracy for the diagnosis of such complex characteristics in the area.

In this classifier, it was found that color, texture and a combination of all features gave very important result. On the other hand from result we observed that shape features gave minimum results comparing with other features. This was due to the size and shape of the *Enset* plant vary at different growing stages and its physical appearance also may vary due to variation of climatic condition, soil fertilities and amount of rainfall.

4.3. Kernel-RBF Classification Model

In the second phase of simulation, the Kernel RBF model classifier was used for the similar features approach practiced in the above experiments.

In this approach, the feature such as texture and color has determined very good performance of model and better patterns of the plant when they examined separately. Due to the homogeneous character of *Enset* disease type, an identification of diseases were difficult in some technique like Kernel- RBF. And also this classifier lowers its accuracy for the combination of three features.

In this, the researcher can generalize that bacterial wilt and black Sigatok shares similar color features. As well as black Sigatok and panama wilt also share a common symptom in color and texture. This indicates that there were features similarities exist between these diseases and cause misclassification results.

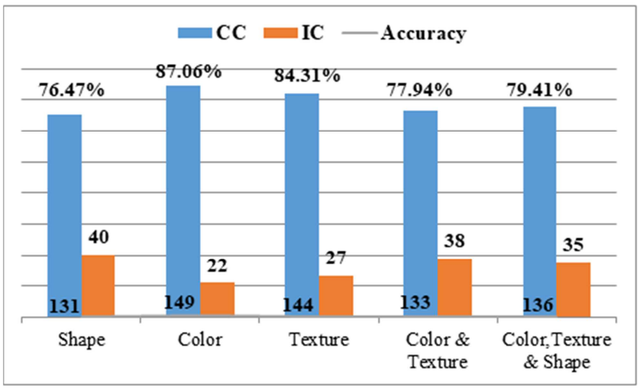

Figure 5. *Experimental Result of RBF Classification Model Using Texture and Color Features.*

5. Conclusion and Future Work

5.1. Conclusion

Image based *Enset* disease diagnosis technique was used to examine the various *Enset* diseases. As the diagnosis of *Enset* plant diseases was based on human inspection that leads to difficulty of identification of its diseases and may significantly affect the others. The diagnosis of *Enset* disease was complex and difficult. So this seeks thorough experience. Moreover it was an expensive diagnosis for many people to see agricultural engineers.

Generally the researcher can conclude the following results from this research work:

i. Intelligent based image processing techniques can play a major role by enhancing, segmenting and extracting the features of the *Enset* image.
ii. Possibility distribution algorithm and Otsu segmentation were effectively detects the affected part of the *Enset* and classifies the type of *Enset* disease.
iii. The rate of accuracy was measured from two simulation phases; Thus, ANN model was found effective to diagnosis the *Enset* diseases than Kernel-RBF. The system achieved an overall accuracy of 91.4% and 79.41% for ANN and Kernel RBF respectively.
iv. Therefore image based *Enset* disease diagnosis technique allows end-users to use the prototype system and appraise the benefits; It can ease the need of agricultural engineers and experienced experts.

5.2. Future Work

Enset diseases diagnosis system was not a straight forward task. Because of the massiveness of the work, limited resources and domain expertise, there are still tasks that can be done in the future to enhance the proposed model.

The researcher recommends future works to further carryout the following points:

i. In this study the researcher has built a system that identifies different type of *Enset* diseases. However, it does not estimate the severity of an identified disease.
ii. The researcher thinks about color, shape and texture as the best image identification technique. However, it is open to investigate emerging image processing techniques that can better distinguish the type of diseases.
iii. It is better to integrate this alternative solution with sophisticated IT based technology such as deep learning algorithms, augmented reality, data mining and data warehousing techniques and other emerging technologies for achieving remarkable performance.

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Biography

Kibru Abera Geinore was currently a lecturer in the Computer Science department at Wachemo University (WCU) in Ethiopia. Prior to his recent appointment at the WCU, he was a senior IT engineer in Ethiopian Customs and Revenue Authority at Mille district. Mr. kibru received his B.Sc. degree in Computer Science from Mekelle University, Ethiopia, and his M.Sc. degree in Computer Science from Arba Minch University, Ethiopia. He has published one article in academic journals in International Journal of Intelligent Information Systems. His research interest areas are: Artificial Intelligence, Data Science, Sustainability Informatics and Software Engineering.