Maize Lethal Necrosis Disease Detection for Maize Crop Real-Time Prediction Yield Modeling through Colour Pixel Feature

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ABSTRACT
Maize Lethal Necrosis Disease (MLND) - is one of the diseases threatening maize production in a large area of East Africa. The disease is initiated by Maize Chlorotic Mottle Virus (MCMV) in blend with viruses of genus Potyvirus, commonly Sugarcane Mosaic Virus (SCMV). The simultaneous infection is the results in intensive to complete yield loss. Inability to predict disease parameters affecting maize crop yield has been a major drawback for the effectiveness and perfection of the existing manual maize crop yield prediction system and procedure in East Africa. Presently, human visual analysis is the furthermost commonly used method for detecting diseases. Due to this method, many errors were observed as the diagnosis is mainly based on the familiarity of the farmers. It consumes time to identify crop diseases founded on visually noticeable characteristics. This research sought to propose a real-time prediction system for maize crop yield using image-based mobile for detecting crop disease affecting crop production using SVM algorithms. In the proposed model, images of maize leaves from mobile were extracted their colour features and identify the Maize Lethal Necrosis Disease (MLND). The presence of SVM due to its fast processing speed as well as accuracy of its output these algorithms requires input training and test data for the model. This prediction model will be integrated into the mobile device for farmers to use. It determines the crop leaf area index that is helpful in predicted yields and its corresponding approximate. Evaluation is also conducted against the proposed model to measure the accuracy of a real-time prediction system in producing the results of crop maize disease. The results show for the SVM, the correlation(R) between estimated Leaf Area for maize and Leaf Area affected in Tunguu area was reported as 0.6959 and 06.099 respectively. So SVM classifiers offer good accuracy as well as perform faster prediction related to naïve Bayes algorithm. Since a combination of Real-time system-based farmers mobile application images collection and Leaf Area index has never been used in East Africa so far for researcher knowledge.

General Terms
In this paper, the real-time prediction yield modeling througha color pixel is considered a general term. During this research, present as well as past studies of different method and technique of real-time prediction in colour features is considered to improve the algorithm in image processing.

Keywords
Maize Lethal Necrosis Disease (MLND), ANN, SVM, LAI, Mobile application, Real-time systems.

1. INTRODUCTION
Cropyield is the measure of crop manufactured per area of land. It is an important metric toapprehend because it helps to understand food security. Achieving maximum crop yield at minimum cost with a healthy ecosystem is one of the main goals of agricultural production. Early detection and management of problems associated with crop yield restrictions can help increase crop yield and subsequent profit; hence, yield estimation is important to numerous crop management and business decisions [1]. The adoption of moreefficient farming practices and technologies can play a crucial role in improving agriculture productivity, household income, food security, and poverty reduction. This is mostly true in Sub-Saharan Africa (SSA), where the majority of the rural households are Smallholder farmers who depend on agriculture for their livelihood [2]. Traditional crop yield prediction is performed by considering and collecting farmers' annual production values and experiences. However, crop diseases, climate, and weather change phenomena may have a considerable impact on crop yield, which leads to uncertainty in predictions [3]. Apart from climate and weather change, a disease acts as one of the contributing factors in poor production and productivity of the most important staple foods including maize [4]. Due to this fact, preventive measures are needed for early detection of diseases. The historical background of the disease in EastAfrica. The disease was primary reported in Kenya; in September 2011, even though its extent at that point recommended that the disease has existed for some time. Agreeing to the Kenyan Ministry of Agriculture, two percent of the maize harvest was affected in 2012. In August 2012, symptoms similar to MLND have also spread rapidly into Tanzania, [5]. Maize is one of the most important staple food and income-generating crop in East Africa as well as perilous for food security in Africa, supporting over 850 million people in sub-Saharan Africa[6]. It has especially significant in smallholder farming systems. However, its yield is low due to several foliar diseases. In Tanzania, maize crops contributed to 50% of the rural household incomes [7]. Currently, the crop is under threat of viruses, specifically those causing lethal necrosis disease (MLND) [8]. In Tanzania for example, Maize crop has bigger potential because it is one of the most dominant crops and the focus of a large government agricultural program [9]. The scope of this study is to address the problem in Tanzania.

1.1 MaizeLethalNecrosisDisease

This disease is caused by simultaneous infection between two viruses, Maize Chlorotic Mottle Virus (MCMV) and Sugarcane Mosaic Virus (SCMV) [10][11]. The disease can occur at any growth stage of maize and all varieties are susceptible to MLND. The major symptoms indications several symptoms include: yellowing and whitening at edges of leaves on a young plant, dying leaf boundaries after ear formation, and wounds on the leaf margins development.

Fig 1: Represents a maize plant symptoms infected with Maize Lethal Necrosis Disease (MNLD).

The common method used for detecting this disease in the field is by using human visual analysis. In this method, many errors were observed as the diagnosis is mainly based on farmer experiences and familiarity. It consumes time to identify crop diseases founded on visually noticeable characteristics [12].

Image processing technique has been considered as well as applied in agriculture aspects due to its nature of accuracy as well as a spread [13]. Nevertheless, little research has been made using the techniques to detect diseases that affect maize like MLND. The delay and misdiagnosis in detection of disease in crops in real-time leads to losses in yields. In that case, the results will affects the food security in the country due to lower yields.

Image-based detection of MLND is constructive in monitoring large grounds of crop and indications that appear on the plant leaves [14]. The real-time prediction will overcome a difficult time distinguishing between MLNN disease and other crop disorders that will lead to timely control of thediseases. Images of leaf diseases are processed by using computer image processing technology as well as extraction of the spots according to theparameters like colour, texture, type, size, and number of spots. A disease thatis diagnosed in real-time principals to the disease being prevented or controlled established on the circumstances of the crop.

Despite the significant recent developments of Machine Learning (ML) and the successful application in many areas, ML techniques have some fundamental limitations when used naively in a purely data-driven fashion [15]. The accuracy of the predictions and their uncertainties produced by the ML algorithms strongly depends on the data quality, model representativeness, and the dependencies between the input and target variables in the collected datasets. Data with a high level of noise, erroneous data, presence of outliers and biases in the data, and incomplete datasets may significantly reduce the predictive power of the models [16]. A human visual investigation is the most common traditional method used by farmers to pinpoint crop disease. The common ways of detecting this disease in maize crops are by using field visits and naked eyes. This method is time-consuming and cumbersome to implement on large-scale farms. This research proposed the use of a real-time prediction system using image-based mobile using Leaf Area Index model (LAI) and Artificial Neural Network (ANN) to detect the diseases affecting maize crop production in Tanzania.

The leaf area index (LAI) model of maize crop plants is the most important factor to determine the yield of maize crops. In this study, the symptoms will be analyzed using image processing techniques [17]. The collected images will be passed through at the level of removing noise, erroneous, outliers, biased data, and incomplete datasets. Support Vector Machine (SVM) algorithms will be used to develop a maize crop yield prediction model using image-processing techniques and sent to a farmer for discussion.

The image-based mobile model will support a quicker method of identifying the diseases affecting maize leaf. The accuracy of the model will provide minor errors of misdiagnosis. As a result, there will be easier detection of the diseases. ANN works at a fast processing speed hence increasing the rate of obtaining the yield.

The algorithm is able to work with partial and unpredictable data, this will be improved the effectiveness of the proposed model. The ANN model has been deep-rooted to provide high levels of accuracy in identification [18]. Rapid and sensitive diagnostic tools are critical for surveillance, early warning, and rapid implementation of prevention strategies [7]. Therefore, this research aims at integrating the benefits of using computer image processing technology as well as ANN in detecting the MLND that affects the leaves of maize crops.

1.2 Study objective

The general objective of this research work will be to have a model that will be determined to predict crop production by level affected by MLND.

1.2.1 Specific Objectives

At the end of this research, the following objectives should be fulfilled:

1) To propose a real-time prediction system for crop yields using mobileimage-based for detecting crop disease affecting crop production.
2) To determine of crop leaf area index and its corresponding approximate.
3) To determine the effectiveness of the system.
4) To evaluate the correlation between maize yields and MLND in a real-time prediction system.

1.2.2 Expected Outputs

The main outputs of this research will be:

1) Seasonal Real-time maize crop yield prediction system for detecting disease.
2) Estimated Leaf Area Index of a productive and healthy crop plant.
3) Mobile Application for maize crop farmers where they will get an estimated seasonal crop yield by sending and receiving predictions tips on improvements to be done at the crop.

1.2.3 Research Question(s)

To reach the goal of a real-time prediction system for maize crop yields, the following research questions must be answered.

The primary research question in this research is:

RQM. Can a real-time prediction model be used to support the increased production of maize crops in Tanzania?

The following are the supporting sub-questions to complement the main research question.

1) What is the best design for a real-time application system for maize crop yield prediction using mobile-based machine learning?
2) What is the estimated Leaf Area Index (LAI) of a healthy crop and its estimated yield?
3) How effective is a real-time prediction system in increasing maize crop production?
4) How accurate is a real-time prediction system in producing results?

1.2.4 Significant of research

The study has two potentialities:

1) Contribution to Computer Science.

2) Contribution to the target users.

The contribution to the field of computer science will be to develop a new approach for having mobile-based machine learning.

The contribution to the field of target users is that the real-time prediction system will be developed and proposed. The system will enable farmers to receive automatic images of their crops in real-time. This will help them in the early detection and management of problems associated with crop yield restrictions. The overall study expectation is to improve agricultural productivity by using emerging technologies.

2. LITERATURE REVIEW

2.1 Computer image processing technology

Computer image processing technology has been applied in several agricultural activities including qualitative sorting out of potatoes color analysis machine [19]. According to [20], machine image application has higher speed and accuracy that significantly leads to crop disease detection. Therefore, computer image processing technology is the most interested area of most researchers on crop disease detection. Due to rising the opportunities of using this method, there is a need to bring mobility as well as flexibility to the existing developed model. Most of the study in this area has focused on those phenomena [21] and [22].

2.2 Computerimage processingImplementation

Computer vision algorithms are affected through various stages. The images that are attained are processed to inaugurate the quantity of the area affected by the disease, colour, boundary as well as texture [23].

Fig 2 presents the systematic of the plant's disease detection as discussed by [24].

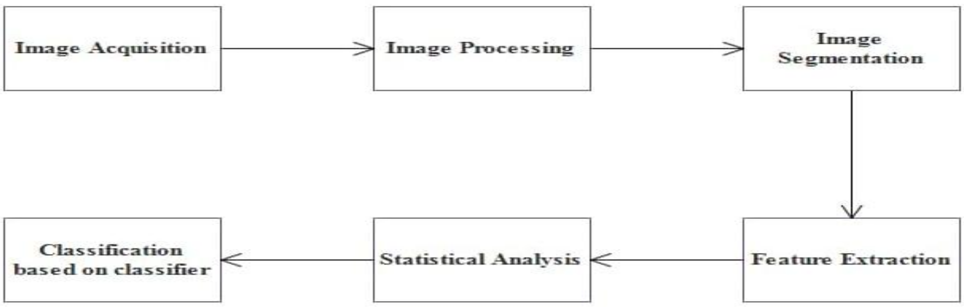

Fig 2: Plants Disease detection algorithm [24]

2.3 Machine Learning Identification Techniques

These techniques are aimed at classifying crop diseases. As agreed by Mitchell as cited by [25] a machine is able to advance performance in a given specific task assumed its experience. Buxton and Breiman as also cited[25] in their work concludedthat machinelearning allows extraction of important data as well as patternsfrom raw data even if the given model is anonymous. Supervised learning as one of the types of Machine Learning includes the processof training a data sample from a data source that accurate identification already allocated [26]. Supervised learning is mainly used to solve identification problems. For example, supervised learning algorithms include, Bayesian Learning, Rule-based learning, and support vector machines as well as Neural Networks. The present research will use supervised learning to classify maize leaf diseases. The algorithm that functional applied in the research was ANN. Though researches on the machine learning model used to classify the model also used in classification of the disease have been conducted [27] [28], nevertheless they only dealt with rice [21] and cotton [28] cultivations.

Some studies show how image processing and machine learning model have been used to detect and classify crop diseases [29][30]. In addition, a study about the detail of the algorithm of image processing [31] has been conducted. The researcher used Otsu thresholding [32] that classifies disease direct on MATLAB 2010a to classify disease on mango, banana, and beans. They remove all the noise in the image before the segmentation acceptable to get high detection accuracy. Furthermore, this method, the real-time detection of the disease system a web-based expert [33] created real-time detect disease on pomegranate fruit [34] agro medical expert system was proposed for detecting papaya disease. Many of these researchers used a conventional method approach. Researchers have used different algorithms and techniques for predicting crop production for many years ago. However, in this research, a combination of ANN [35] and SVM [36] algorithms will be the choice of this study based on advantages highlighted by researchers. ANN algorithm implementation will use feed-forward backpropagation to train the predicting model on how to predict future maize yields based on currently collected data. Support Vector Machine algorithm will be used to improve the results of ANN and assist in classifications of seasonal yield forecasts. Support vector machine was trained to estimate the LAI for wheat, rice, corn, and soybeans but the results were estimates from the WCM [37]. Currently, many machine-learning algorithms have been used for feature selection; they are usually conducted by regression in LAI estimation.Conversely, no indication suggests that is the optimal solution [38].

3. RESEARCH METHODOLOGY

In this paper, they present a real-time prediction system for maize crop yield using image-based mobile for detecting crop disease affecting crop production using SVM algorithms. In the proposed model, images of maize leaves from mobile were extracted their colour, features and identify the Maize Lethal Necrosis Disease (MLND). Presence of SVM due to its fast processing speed as well as accuracy of its output. These algorithms require input training and test data for the model. This prediction model will be integrated into the mobile device for farmers to use. It determines the crop LAI and its corresponding approximate. Fig 2 and 4 present the proposed model of present research, whereby Fig 3 presents a flowchart of the system of the research, and Fig 4 presents the demonstration working of the proposed model.

Fig 3: Methodology flowchart of this research

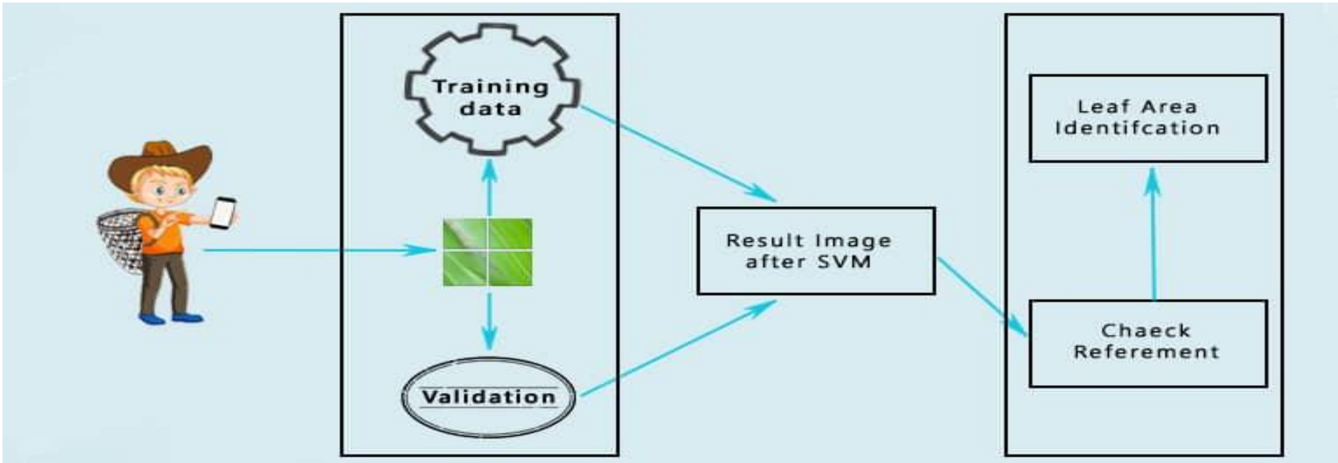

Fig 4. Demonstrates how the proposed model works. The farmers make use of their mobile phones to take images of the maize leaf. Pixel features of the images will be used as the input for SVM classification algorithm. The classification model will be trained and validated to work. The maize leaf disease identification denotes the output of the model. The discriminative classification algorithm will automatically detect unhealthy regions of the leaf images. Then an algorithm that has beendesigned to differentiate the classes will be determined health and unhealthy leaf. The following are the steps in which the chosen algorithm follows:

Step 1: Segmentation that will divide leaf image into foreground and background.

Step 2: An SVM algorithm will be applied to predict the class of every pixel that is belonging to the foreground.

Step 3: Advance refinement by neighborhood-check that neglects all incorrectly classified pixels from the second step.

Step 4: Calculate the Leaf Area of infected region as well as determine the crop leaf area index and its corresponding approximate.

The following Fig 5 shows an overview of the proposed algorithm, whereby an input image is the Maize leaf that has a monochromatic background. First, step segmentation method is pragmatic to acquire the pixels that belong to leaf. Second step, each pixel that is belonging to maize leaf is classified by using a linear SVM classifier. Third step, the output from SVM classifier is further refined through a neighborhood-check method to obtain the final output image. In addition, Forth step evaluates the results by introducing Leaf Area of a leaf as well as leaf area of affected part.

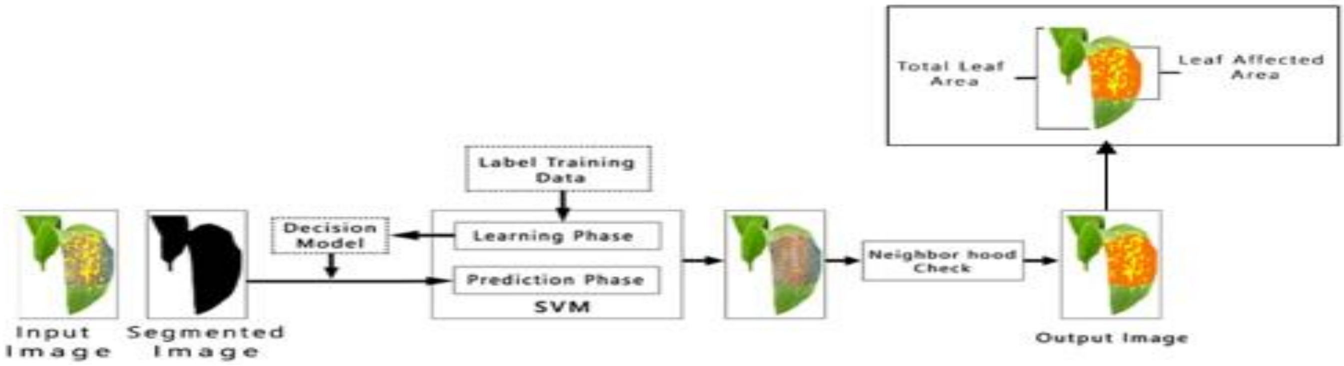

Figure 5: An overview of the proposed algorithm

3.1 An SVM algorithm model

In this study, the SVM classifier was assessed for LAI estimation and has successfully practiced classification as well as function estimation. The goal of SVM is to find out the hyper-line that will maximize the minimum distance between data points.

In the feature space, SVM model takes the form as:

$$y(x) = \omega^t \varphi(x) + b$$

Weight vector Nonlinear mapping is the bias

Appropriate, for the basis of SVM regression is to fit a function that will be between the training and test data such that maximum deviation between the estimated and observed values should be less than a precision parameter (ϵ).

The equation below shows the problem is transformed into a quadratic optimization problem is expressed by introducing the slack variables.

$$min \tfrac{1}{2}\omega^t\ \omega + C\sum_{i=1}^{l} \epsilon i \ \rightarrow \text{a precession parameter}$$

C=Constant trade-off parameter between the error and margin

$$\text{Subject to} \begin{cases} yi - f(xi, \omega) \le \varepsilon i \\ \varepsilon i \ge 0, i = 1.2{,}3 \ldots .n \end{cases}$$

Where w is the normal vector, f () is the fitting function, xi is the input training data, yi is the model response and n is the number of training data.

In this study, the SVM model was trained based on intensity for parallel (VV) and perpendicular (VH) with LAI set as the response.

3.2 Colour pixel feature

When Optimal separating hyperplane and the maximum margin separating the data between the classes each pixel now is belonging to a homogenous region correspond to a part of an object.

Now it'scolour the extracted pixel-level image feature through each pixel's color measures only intensity of light in that point by perceiving an average of the intensity for each colour channel.

3.3 Predicting yield Model equation

The leaf area index (LAI) model of maize crop plants is the most important factor to determine the yield of maize crops. In the proposed model, they have to introduce leaf Area of a leaf as well as leaf area of affected leaf part.

For that case, it will predict the maize yield by the following equation:

$$P = \sum_{i=1}^{n}\{(\text{LA}) + \sum_{i=1}^{n}(LAa)\}/LAa*100$$

P,predict yield i.e 0%≤P≤100% LAI,The Leaf area index

LA->Leaf Area,LAa->Leaf Area affected,n->maximum number of image

3.4 The material and method

This subsection focus on discussing computer image processing technology as well as the different machine learning techniques that support the detecting of MLND diseases. The methods, models, algorithm that was intently related several gaps as well as strengths of the reviewed works shown below:

As per this research of detecting MLND through pixel-based classification, the algorithm has been tested widely on more than 100 infected maize leaf images. The testing images were obtained from one of the firms that plant Maize crops at Tunguu, Zanzibar. The viruses infected most of the plants. The input maize leaf images are the infected with monochromatic background and the output is the classified that marked unhealthy region. The current study involved six farmers by given six(6) mobile phones and asked to capture and infected images that will be detected by a prediction model that is integrated into mobile devices with the presence of an SVM algorithm, the experiment was conducted from 20 February 2021 to 1 June 2021.

4. EXPERIMENTAL RESULTS

This section presents the findings of the study in which Fig 5 shows output of some of those images from the SVM classification algorithm. The results obtained from this algorithm were convincing and be easy to predict the maize yield by calculating the LAI as well as Leaf Area of marked unhealthy regions. There are some isolated pixels, for the visual perception of human observation to resemble with, they extend the results by using neighborhood-check that will neglect the isolated pixels for that case, and the proposed model will have more accuracy than the probabilistic model in their algorithm.

The evaluation of this model is compared with the naïve Bayes algorithm that is not always possible with real-time data. The conducted experiments prove that higher accuracy could be succeeded by using the SVM classifier algorithm reason is very computationallyefficient, and having amendments of numerous parameters even by using multi-class SVM. It was also found that there are more robust in separating the data rather than Bayes like classifiers.

Fig6 presents an LAI and leaf area of unhealthy region. It demonstrates a high number of pixels are marked as unhealthy after applied the algorithm. In addition, neighborhood check method to remove isolatedpixels now matches with the visual perception of farmer observers.

Fig 6: The maize leaf that is unhealthy but with the human eye perceives them as healthy

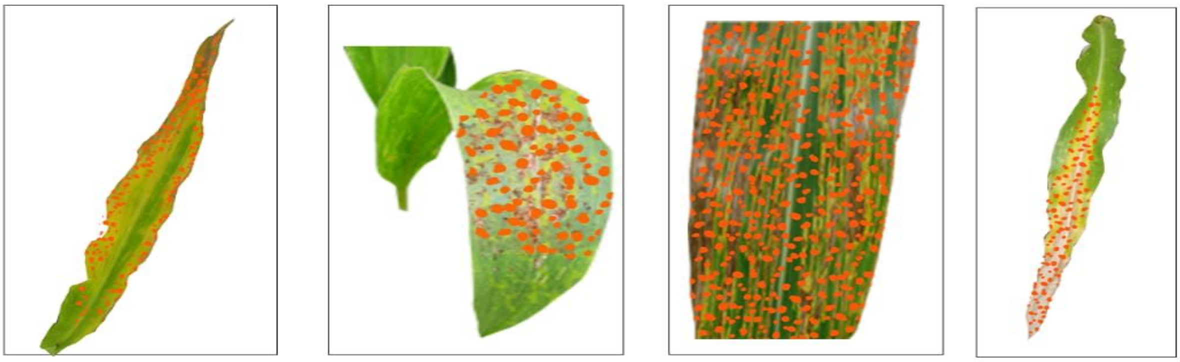

Fig 7: Output from the SVM classifier algorithm

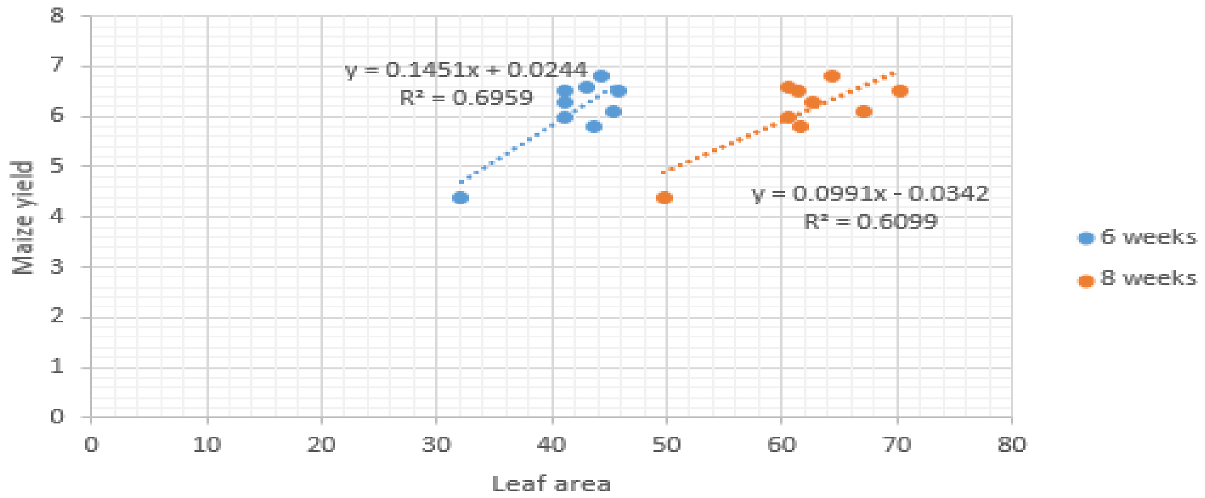

Fig 8: Relationship between maize grain yield for 6 weeks and after effect in 8 weeks

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.780958494
R Square	0.609896169
Adjusted R Square	0.55416705
Standard Error	3.761154012
Observations	15

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	154.8160435	154.8160435	10.94394	0.012974277
Residual	7	99.02395652	14.1462795		
Total	8	253.84			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	24.39673913	11.43574237	2.133376072	0.070319	-2.644494602	51.43797286	-2.6444946	51.43797286
maize yield	6.15326087	1.860023635	3.308162732	0.012974	1.755003874	10.55151786	1.75500387	10.55151786

Fig 9: Regression statistics from the result data set

The results from Fig 8 and Fig 9 show that growth maize yield is affected when days are moving, this shows the Leaf is affected after some time and yield prediction is decrease. This makes the leaf are not healthy and have been affected concerning time.

4.1 Evaluation of the model

During the experiments, six farmers evaluated the system; four android phones were used to test the system. The system was evaluated in terms of four testing criteria completeness, clarity, correctness, and consistency, as shown below:

i. Completeness: prototype was evaluated and research objective was met. It compiles without error.

ii. Clarity: system was friendly. The following criteria were observed.

Farmers able to understand the meaning of each image

- it takes few seconds to estimate seasonal prediction crop yield

iii. Correctness: prototype was evaluated for validity and acceptability of components related to the technology used. The following criteria were observed.

- Its output displayed on phones correctly
- Its image compatibles with different phone screen sizes

iv. Consistency: prototype was evaluated to find if it met user's assumptions. The following criteria were observed.

- Images understandable for each person.
- The model runs on Android mobile platforms.

5. CONCLUSION

This research puts its importance on taking advantage of computer image processing technology as well as machine learning algorithms for the detection of the MLND. At the end of this research, a real-time prediction system for maize crop yields was proposed. The system is expected to use mobile image-based for detecting maize crop disease affecting crop production plantations. They presented an automatic pixel-based classification method is used for detecting affected areas (unhealthy regions) in maize leaf images. This method has been tested and results were obtained that are promising and accurate. A linear SVM algorithm has been used and classifies each pixel with help of neighborhood check technique. It has determined the maize crop leaf index as well as its corresponding techniques. Analysis of image data using image-processing techniques was done. Finally, the proposed system was evaluated including its benchmark with existing methods in the current practice. The Regression analysis

R>0.69 shows that there is a strong correlation between the variables as well as a relationship between two continuous variables. However, after some time Regression analysis drops down which shows ongoing that leaf area has been affected with MLND for time. . This research has added an edge and highly contributes to the use of mobile devices for image-based prediction tasks. Since a combination of Real-time system-based farmers mobile application images collection and LAI index has never been used in Tanzania so far for researcher knowledge.

6. RECOMMENDATION

In this research, it mainly relies on colour features but possible for an extension to other features.

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