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Image Optimization Technique Using Local Binary Pattern and Multilayer Perceptron Classification to Identify Potassium Deficiency In Cacao Plants Through Leaf Images

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ABSTRACT

Cocoa plants (*Theobroma cacao, L.*) are the best plantation crops in Indonesia that play an important role in the economy. However, in cultivation, cocoa farmers often face problems that can cause a decrease in cocoa production, one of which is the lack of potassium nutrients. Therefore, how to implement digital image processing which can help analyze image objects in the form of normal leaf characteristics and potassium-deficient leaf characteristics using the *Local Binary Pattern* (LBP) method for image feature extraction and classification using the *Multilayer Perceptron* (MLP) method in identifying potassium deficiencies in cocoa plants based on their leaf characteristics. In the image object in the form of leaf characteristics, each will be identified with 250 in the background dataset and 100 in the non-background dataset. So that the feature extraction process by LBP can be analyzed using the MLP parameter approach in the form of variations in the *Learning_rate* network and several solvers. In the case study conducted as the methodology applied starting from data collection, algorithm development to validation and measurement using ROC, it was found that the results of the paper using the LBP method and MLP classification showed that the best accuracy results in testing the background dataset using the *learning_rate* network 10(-4) with Solver were 86.66% and the best accuracy in testing the non-background dataset using the *learning_rate* network 10(-3) with *Solver adam* was 80.00%.

1. INTRODUCTION

Cocoa (Theobroma cacao L.) is one of the potential foreign exchange-earning plants. One of the leading cocoa-producing areas in Indonesia is Southeast Sulawesi Province. It is one of the prima donna plants because it makes a real contribution to increasing farmers' income, so many farmers' welfare increases because of this cocoa plant, as evidenced by the many people in Kolaka who go on the hajj because they grow cocoa plants [1]-[3].

Processed products known as chocolate are produced from the seeds of this plant. Cocoa is also a plantation crop that continues to receive attention for development. Indonesia is also one of the world's third-largest cocoa-producing and exporting countries after Ghana and Ivory Coast.

Indonesia is the world's 3rd largest cocoa producing and exporting country after Ivory Coast and Ghana. The quality of cocoa beans is influenced by the good or bad of the fruit itself. One of the parameters of the quality of cocoa fruit is the presence or absence of disease caused by pests or pathogens that attack cocoa plants. However, disease checking in cocoa is still done manually by humans with a relatively low level of accuracy [4]-[12]. This indicates the important role of cocoa as a source of employment and income for farmers. In addition, the area and production of cocoa in Indonesia have increased rapidly in the last decade, at a rate of 5.99% per year. However, along with the increasing area of cocoa development, lately, cocoa production and productivity in Indonesia have continued to experience a very significant decline [13]-[16].

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One effort can be made is fertilization; the fertilizer given can be organic fertilizer and inorganic fertilizer in the nursery medium. Fertilization aims to improve soil fertility so that cocoa can grow faster, fertile, and healthy. Fertilization can add nutrients unavailable in the soil in sufficient quantities, such as nitrogen, phosphorus, and potassium [17]-[21].

In cocoa plant nurseries, using inorganic fertilizers also plays an important role in plant growth and getting good seed quality. The compound organic fertilizer that is often used is NPK fertilizer. NPK fertilizer is an essential nutrient necessary for plant growth, but NPK compound fertilizer also has weaknesses, such as being easily dissolved and evaporated; economically, the costs used are quite expensive.

However, at present, the shortcomings of NPK fertilizer can be covered by the advantages of organic materials provided, such as not easily evaporated, being environmentally friendly, being used as an additional / substitute for nutrients for plants, and improving soil structure. Therefore, organic and inorganic fertilizers can show good interactions and directly impact plant growth [22]-[26].

Cocoa plants are plantation crops on dry land; if managed properly, they can produce high yields and be economically profitable. However, farmers often experience a decrease in harvest due to diseases and pests that attack cocoa. These cocoa diseases can attack the leaves, causing spots on the leaves and yellow or brown leaves. Healthy leaves on cocoa plants are green without any brown spots on the top so cocoa leaves that are affected by the disease are marked with brown spots on oval leaves that are evenly distributed on the surface of the leaves with a gray or white center point [27]-[29].

Plant diseases cause production and economic losses, especially in agriculture. This disease often causes visual symptoms on the surface of the leaves, such as spots, streaks and discoloration. Determining the disease is usually done conventionally by examining the physical leaves of rice plants. Meanwhile, it is possible to carry out this identification using digital technology devices, namely checking for symptoms of damage to leaves based on digital images [30]-[34].

The very easy image acquisition encourages the possibility of various kinds of noise, so a pre-processing stage is needed to improve the quality of the image to be studied. Improving image quality aims to adjust an image to provide appropriate results. The results suitability can affect the image's appearance and analysis for further action [35]. The results of digital image processing are also used as a consideration for making a decision. Improving the quality of digital images can be done with various methods or techniques that are carried out before conducting further research. Based on the statement that has been explained above, this study aims to implement image processing using LBP and Multilayer Perceptron classification to identify potassium deficiencies in cocoa plants through leaf images.

There are several differences from previous related research with this research, namely where the previous related research aims to find food recipes based on food images using 3 methods, one of which has similarities to the method that will be used by the current researcher, namely the LBP method by identifying potassium deficiency. This can be seen in the following explanation.

First, Saidah et al. (2020) conducted a study on "Comparative Analysis of LBP and CLBP Methods in Individual Recognition Systems Through Iris." The study aims to compare the performance of the LBP and CLBP methods in recognizing individuals through their irises. By using the "Compound Local Binary Pattern (CLBP) method and Neural Network as a classifier with the method used to recognize individuals based on physical characteristics, character, or behavior that distinguishes one individual from another is called biometrics where the iris is one of the biometric characteristics that is often used for the individual recognition process. The study results showed that the CLBP method produced the highest accuracy of 89.71%, while the LBP method produced an accuracy of 87.43% in previous related research where the researcher aimed to determine the comparison of performance in recognizing individuals through irises using the LBP and CLBP methods. Meanwhile, this study will identify Potassium deficiencies through leaf images, where one of the methods is the same as the method used by researchers, namely the LBP method, which aims to help farmers find out about nutrient deficiencies in cocoa plants [36].

Second, Irfan et al. (2017) have researched "Vehicle Classification System Based on Digital Image Processing with the Multilayer Perceptron Method," where the research consists of 2 stages of digital image processing, namely the detection & classification process. The detection process uses the Haar Cascade Classifier with training data in vehicle images and testing data in vehicle images on toll roads taken randomly. Meanwhile, the classification process uses Multilayer Perceptron using the processed detection results. The vehicle classification process is divided into 3 types: Cars, Trucks, and Buses. So that the classification is assessed or estimated using the accuracy parameter. The test results in the vehicle detection process showed an accuracy of 92.67%. Meanwhile, the classification process is carried out with a trial-and-error stage to evaluate the parameters that have been determined. The study's results showed a classification system with an average accuracy value of 87.60%. The study aims to implement digital image processing to create a system that can classify vehicles based on their type [37].

The related research differs from the research that will be carried out, namely, where the previous study aimed to implement digital image processing to create a system that can classify vehicles based on their type using the Multilayer Perceptron (MLP) classification. The research will aim to identify potassium deficiencies through leaf images using the Multilayer Perceptron classification. And has similarities in the classification used.

Third, Amerta et al (2019) researched "Searching Food Recipes Based on Food Images Using Simple Morphological Shape Descriptors, Cie L * A * B * Color Moment and Local Binary Pattern" recipe searches are generally limited to using the title or name of a food, and to overcome these limitations, image-based searches are needed. Image-based search requires image feature extraction. Therefore, image-based search will use 3 feature extraction methods and color feature retrieval, which is done using the CIE L * a * b * Color Moment method. In the shape feature, the method used is Simple Morphological Shape Descriptors (SMSD), and in the third feature, the texture is extracted using the Local Binary Pattern (LBP) method. The goal is to help get recipes more easily, but feature selection from images that will achieve high accuracy will be a problem [38].

Thus, this study aims to make it easier to predict the next amount. So, using the Multilayer Perceptron method is the same as the method used by current researchers but has different goals and results. Using the LBP and Multilayer Perceptron methods, researchers will now identify potassium element deficiencies through leaf images. So that it can implement image processing using LBP and Multilayer Perceptron.

2. METHOD

This study explores leaf image optimization using digital image processing. Digital Image Processing is a discipline that studies image processing techniques. The image referred to here is a still image (photo) or a moving image (from a webcam) [39]. Digital here means that image/picture processing is done digitally using a computer [40]. Mathematically, an image is a continuous function with light intensity in a two-dimensional plane. In order to be processed by a digital computer, an image must be presented numerically with discrete values. A digital image can be represented by a two-dimensional matrix f(x,y) consisting of M columns and N rows, where the intersection between columns and rows is called a pixel (pixel = picture element) or the smallest element of an image [41].

The materials used in this study are cocoa leaf image data using background and non-background where there are two types of leaves, namely normal and potassium deficiency, with the amount used each in the background data 250 and non-background data 100 to identify whether the plant is deficient in potassium nutrients or other nutrient deficiencies through leaf images.

2.1. Data Collection Technique

In data collection techniques, it is to determine how to collect data that will be used for research, the methods used are:

2.1.1. Observation

Observation is a data collection technique that involves watching and recording the behavior, actions, or events of people, objects, or phenomena in their natural or controlled settings. It can gain insights and identify problems, opportunities, or trends [42]. This technique is carried out on cocoa plantations to directly observe each characteristic of cocoa leaves by looking at the existing data and to obtain accurate data that can be used as a reference in the research.

2.1.2. Literature Study

Looking for references as complementary and comparative data and concepts in the system of identifying types of cocoa plants based on leaf images. The data is in the form of journal books, previous theses, internet downloads, and so on which are informative and relevant. A literature review involves researching, reading, analyzing, evaluating, and summarizing scholarly literature (typically journals and articles) about a specific topic [43]. The results of a literature review may be an entire report or article OR may be part of an article, thesis, dissertation, or grant proposal. A literature review helps the author learn about the history and nature of their topic, and identify research gaps and problems [44].

2.1.3. Interviews

An interview is a qualitative research method that asks questions to collect data from one or more people. Interviews are useful for gathering detailed information, examining processes, and understanding complex topics. They can be conducted in various ways, including face-to-face, over the phone, or via video conferencing [45]. Conducting interviews with one of the cocoa experts, Agrotechnology Lecturer, Mr. Dr. Harli A. Karim, SP., MP, and farmers in the village, where the village is famous for its vast cocoa plantation area.

2.2. Data Analysis Techniques

The analysis stage is carried out on the running system, and then a proposed system is needed; this system is made from a manual system to a system that uses training and trans-flow data. This system aims to facilitate data disbursement, input, and reporting. Then, an analysis of the input, output, and system processes is carried out. The analysis aims to identify whether the system used so far is still widely used to change itself from manual to system.

2.2.1. Data validation with Receiver Operating Characteristic (ROC)

Testing the results of recognizing cocoa leaf characteristics, both those classified as usual and those affected by the disease was carried out separately to measure its performance on two types of data models, namely Grayscale and Threshold Binary data. This test is carried out to measure the accuracy of the two data approaches. Accuracy measurement uses the Receiver Operating Characteristic (ROC) technique.

To determine the desired model parameters, ROC users must be in accordance with the characteristics of the desired classifier model. The broader ROC system has many models that can be measured from a data analysis such as True positive rate (TPR)/ sensitivity, False negative rate (FNR)/ Specificity, Miss rate/ False positive rate (FPR)/ Fall-out, Specificity (SPC)/ True negative rate (TNR), Prevalence, Positive predictive value (PPV)/ Precision, False omission rate (FOR), Accuracy (ACC), false discovery rate (FDR), and Negative Predictive Value (NPV), with variations of the formula as follows:

$$True\ positive\ rate/Sensitivity = \frac{\sum True\ positive}{\sum Condition\ positive} \quad (1)$$

$$False\ negative\ rate\ (FNR)/Specificity = \frac{\sum True\ negative}{\sum Condition\ negative} \quad (2)$$

$$Miss\ rate/False\ positive\ rate\ (FPR)/Fall\ -out = \frac{\sum True\ positive}{\sum Condition\ negative} \quad (3)$$

$$Specivivity\ (SPC)/True\ negative\ rate\ (TNR) = \frac{\sum True\ positive}{\sum Condition\ negative} \quad (4)$$

$$Prevalence = \frac{\sum Condition\ negative}{\sum Total\ population} \quad (5)$$

$$Positive\ predictive\ value\ \frac{PPV}{Precision} = \frac{\sum True\ positive}{\sum Predicted\ condition\ positive} \quad (6)$$

$$False\ omission\ rate\ (FOR) = \frac{\sum True\ negative}{\sum Predicted\ condition\ negative} \quad (7)$$

$$Accuracy\ (ACC) = \frac{\sum True\ positive + \sum Condition\ negative}{\sum Total\ population} \quad (8)$$

$$False\ discovery\ rate\ (FDR) = \frac{\sum False\ positive}{\sum Predicted\ condition\ positive} \quad (9)$$

$$Negative\ predictivitevalue(NPV) = \frac{\sum Condition\ negative}{\sum Predicted\ condition\ negative} \quad (10)$$

From the formula, if a classification with two-class predictions (binary classification) is known, where each positive result is labeled positive (p) and the negative result is labeled negative (n). From the two classes, there will be four possible results from the binary classifier [46].

The system framework is a general cycle to describe the goals to be achieved. Where this system framework contains input, process and output. The following is the system framework for the identification of potassium nutrient deficiencies in cocoa plants through leaf images.

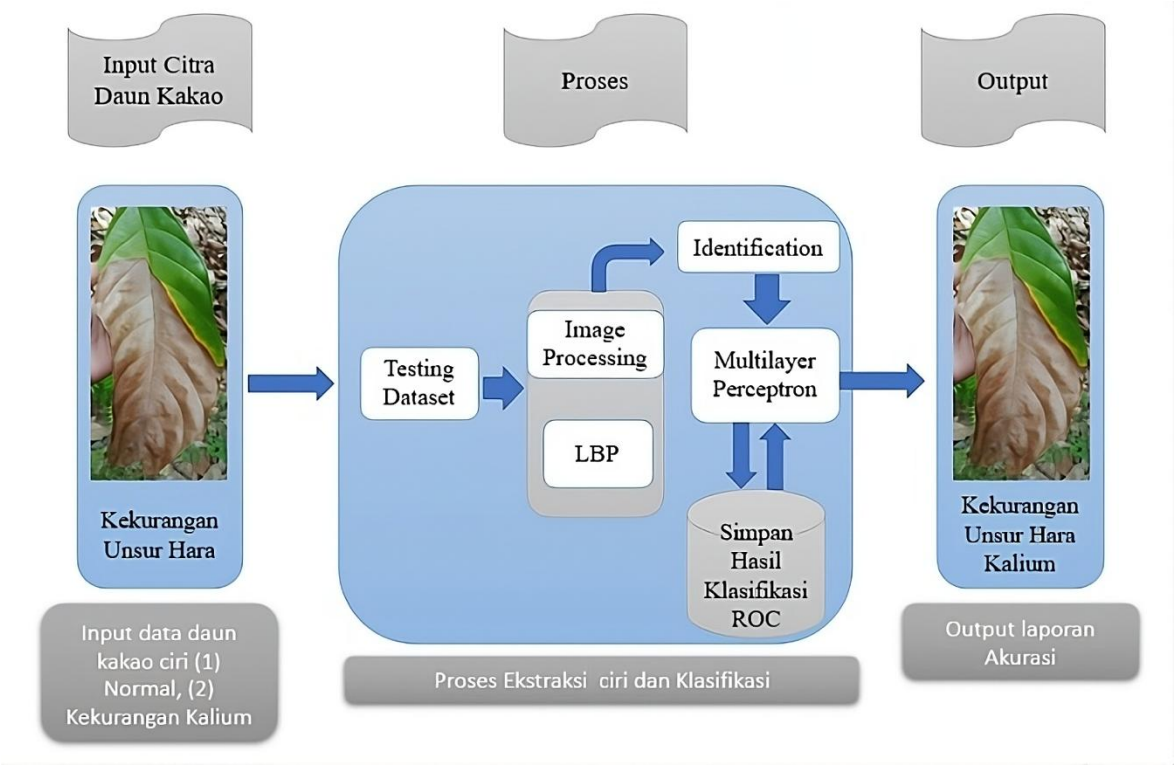

Figure 1. System Framework

The system framework above explains that the user will input cocoa leaf image data characterized by regular and potassium deficiency. Then, in the dataset testing process, where previously the image processing and feature extraction process was carried out with LBP identified then, Multilayer Perceptron (MLP) classification was carried out. The classification results were saved in ROC form so that it would produce a good accuracy report when testing and would display the results that the leaves were deficient in potassium nutrients. In data collection using a smartphone camera, in this case, it was conditioned on a white background and non-background with the number of datasets used each on the background of 250 image data and non-background 100 image data, where normal leaves were labeled (0) and leaves deficient in potassium were labeled (1).

The temporary system design of the identity system is a description and design before building an image optimization technique system using LBP and Multilayer Perceptron classification to determine potassium deficiency through leaf images using two types of data, namely background, which has 250 data and non-background has 100 data, where the data has two data characteristics, namely normal leaves and leaves lacking potassium. First, the image feature extraction process using LBP can display the results of storing the dataset in CSV format. Then, the dataset in the form of a CSV dataset is processed using Multilayer Perceptron to produce an accuracy value.

3. RESULTS AND DISCUSSION

Based on the results of feature extraction, it is known that the dataset class division where the class can be divided into two classes, namely the regular class (0) and the potassium class (1). Then, the list is combined into one variable so that the result becomes a loaded dataset in the form of a column containing a list of image files that display a Filename and label. Then, display one of the filename images with an axis, and can also display several filename images with the same size by changing the size to 250, then extract the LBP feature from one image file that is read and change the color space to grayscale and also display the LBP histogram. Then, an empty variable is created to read and store LBP data and table data into a dictionary variable; then the dictionary variable is saved into the LBP dataset form with CSV format.

Meanwhile, the results of the Multilayer Perceptron classification are known to load this dataset, displaying the contents of the LBP dataset format that has been saved in CSV format through the feature extract process and displaying the X and Y datasets on the loaded dataset, then carrying out the train test split process so that it displays the size of the train data and test data, then configured into the form of a Multilayer Perceptron (MLP) so that it is trained and tested with the MLP model which will then display the accuracy value and Classification report and will also display the Confusion Matrix.

The multilayer perceptron (MLP) classification process results in a confusion matrix and classification report, as shown in the sample output image and precision table below.

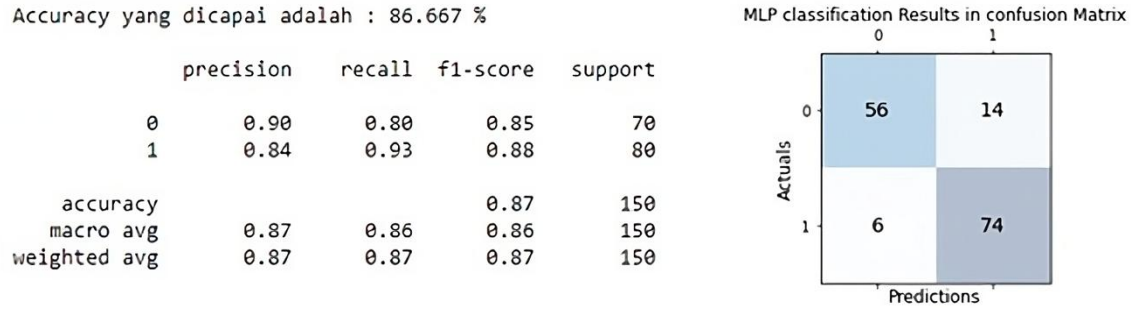

Figure 2. Sample output of MLP classification background.

The calculation of the background accuracy value is shown in the following formula:

$$Accuracy(ACC) = \frac{\sum True\ positive\ +\ \sum True\ negative}{\sum Total\ population} = \frac{56+74}{56+14+6+74} = \frac{130}{150} = 86.66 \quad (11)$$

Table 1. Background precision model

Category	Model Background			
	Precision	recall	f1-score	Accuracy
Normal	0.90	0.80	0.85	86.66%
Potassium deficiency	0.84	0.93	0.88	

In Figure 2 and Table 1 above are examples of samples taken from background data that has 250 data using solver with a learning rate of 10(-4) which produces the best accuracy, namely 86.66%.

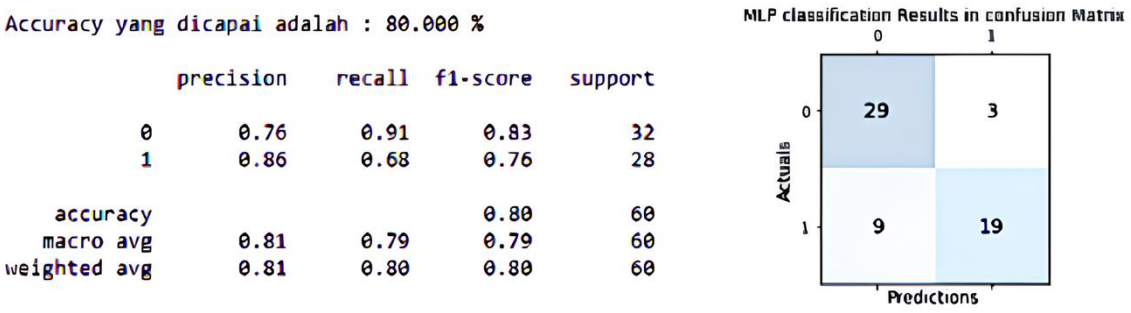

Figure 3. Sample output of non-background MLP classification

The calculation of the non-background accuracy value is shown in the following formula (19):

$$Accuracy(ACC) = \frac{\sum True\ positif\ +\ \sum True\ negatif}{\sum Total\ population} = \frac{29+19}{29+3+9+19} = \frac{48}{60} = 80.00 \quad (12)$$

Figure 3 and Table 2 above are examples of samples taken from non-background data with 100 data using Adam solver with a learning rate of 10 (-3), which produces the best accuracy of 80.00%.

The results of this system test are to display the accuracy value or results. For a comparison of the accuracy value in the LBP dataset test using background and non-background data which have 2 characteristics of cocoa leaf data, namely normal leaves and leaves lacking potassium, in this test each has an accuracy value which is found in the network learning rate 10 (-4) with the solver of 86.66% in the background dataset testing with 250

data while in the non-background dataset testing with 100 data it has an accuracy value which is found in the network learning rate 10 (-3) with adam solver which is 80.00%. It also displays the Confusion Matrix and Classification Report.

The results of comparing the accuracy values of background and non-background data using the LBP method and Multilayer Perceptron classification. This shows the results of the accuracy values obtained at the network learning rate, namely 10 (-3), and 10 (-4), using several solvers, namely blogs, sgd, and adam. The solver is a parameter that determines the algorithm for optimizing weights across nodes. And the learning rate init is float, default = 0.001 or 10 (-3) and 0.0001 or 10 (-4) at the initial learning rate used. This controls the step size when updating the weights. It is only used when solver = sgd, adam, and lbfgs. Where adam is similar to sgd in that it can automatically adjust the amount to update parameters based on adaptive estimates of low-order moments. At the same time, lbfgs is a solver approximating a matrix representing a function's second-order partial derivative.

The graph above shows that the graph displays the results of the accuracy value with each case or different data where graph 4. shows the accuracy value with the background data case and graph 6. shows the results of the accuracy value with the non-background data case so that it produces graph 6. where the image shows the results of the comparison of the highest accuracy values on the background and non-background with different solvers.

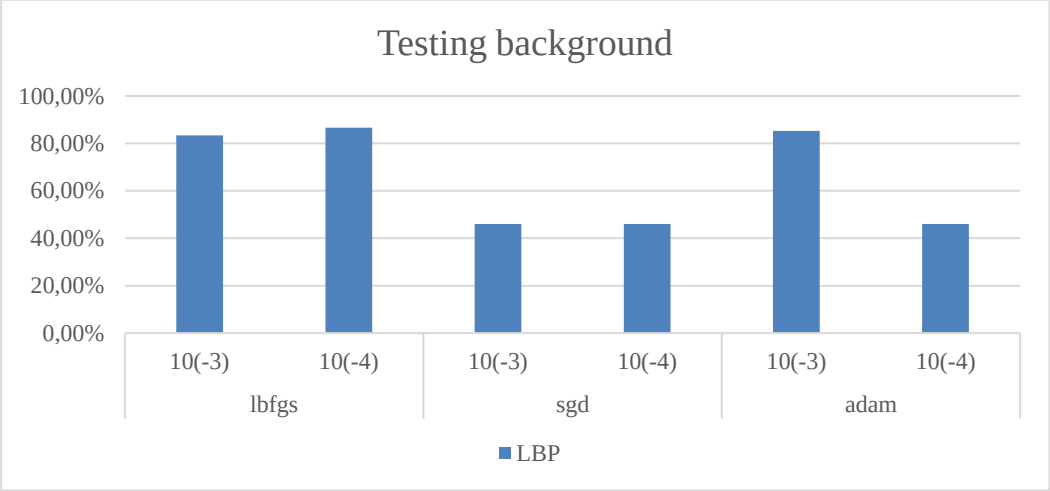

Figure 4. Background graphic

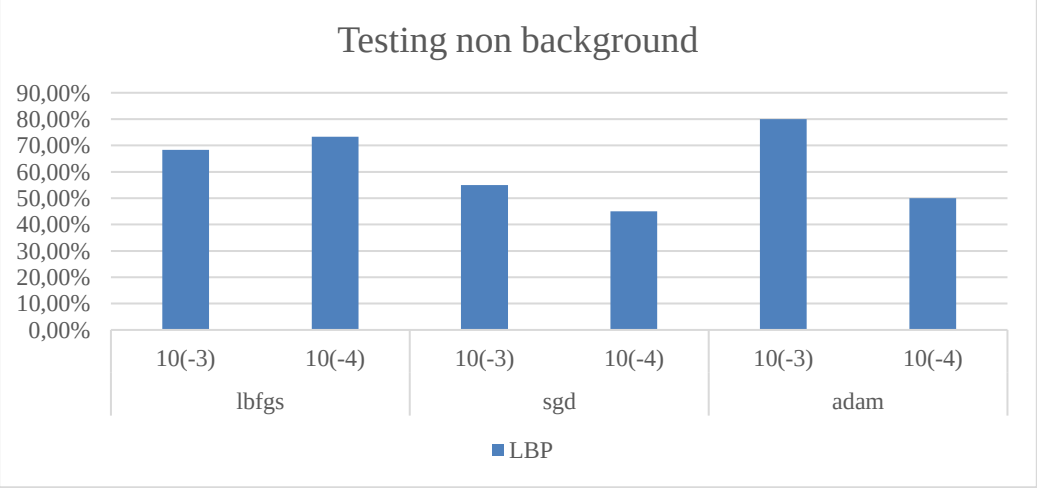

Figure 5. Non background graphic

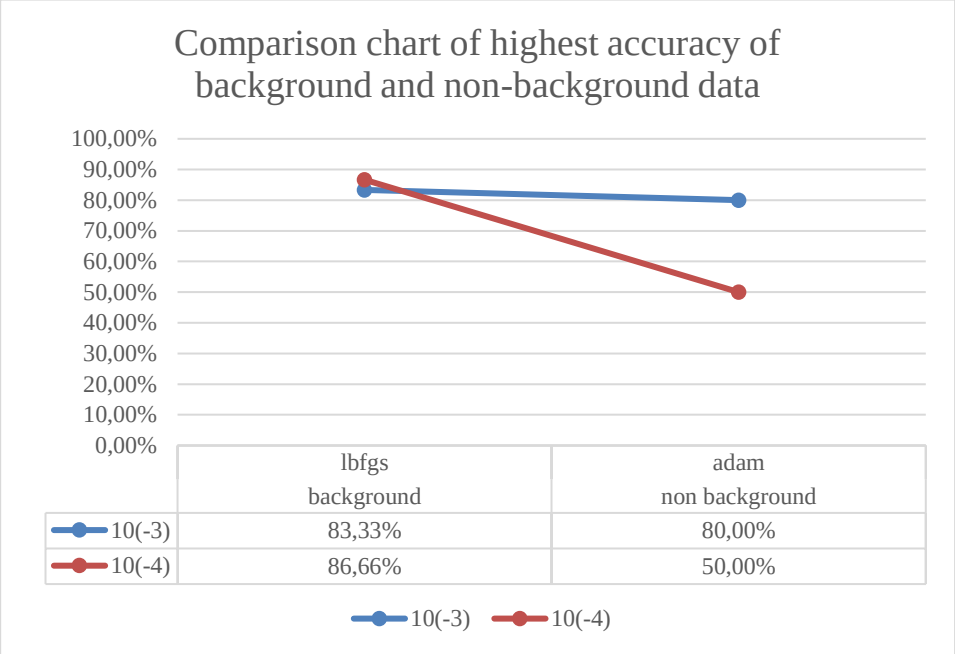

Figure 6. Comparison graph of the highest accuracy of background & non-background data with different solvers

4. CONCLUSION AND LIMITATION

Based on the results of the algorithm development as the research flow carried out, this study aims to implement image processing using LBP and Multilayer Perceptron classification in identifying potassium deficiencies in cocoa plants through leaf images. As in the study, the feature extraction process has been carried out using the LBP method, resulting in a dataset in the form of a CSV file and then entering the classification stage using MLP. So that the classification results with the development of the algorithm as in the method used as feature extraction with quite varying accuracy depending on the solver and the use of the learning rate network, it was obtained that the best accuracy in testing the background dataset using the learning rate network 10 (-4) with the lbfgs solver was 86.66% and the best accuracy in testing the non-background dataset using the learning rate network 10 (-3) with the adam solver was 80.00%.

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