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Citrus Tree Nutrient Deficiency Classification: A Comparative Study of ANN and SVM Using Colour-Texture Features in Leaf Images

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Abstract: Nutrient deficiency in Citrus reticulata (mandarin orange) plants is a critical agricultural issue that has far-reaching implications. Such deficiencies not only compromise the overall health and vigor of the mandarin orange trees but also render them more susceptible to diseases and pest infestations. Addressing this concern is of principal importance to ensure sustainable citrus cultivation and enhance crop yield. In this research, we propose a comprehensive approach to tackle the pervasive problem of nutrient deficiencies in Citrus Reticulata var. Fremont leaves. Our approach leverages cutting-edge techniques in image processing and machine learning to provide accurate and efficient detection of these deficiencies. The image data is divided into four classes: N Deficiency, P Deficiency, K Deficiency and Normal. The file sizes are compressed using a lossless compression method, resulting in an average file size reduction of 96.99%. The second stage involves applying segmentation processes to the images using the Canny and Sauvola methods.Third stage involves extracting colour and texture features from the images. The feature values will be used for the classification process in the next stage. The segmentation process employs two methods, namely Canny and Sauvola, which effectively separate the leaves from the background. The detection process is evident in the feature extraction phase, which utilizes two features: colour and texture.The fourth stage involves the classification process based on the segmentation results methods, performed separately using Artificial Neural Network (ANN) and Support Vector Machine (SVM) methods. These process results in four datasets: Canny-ANN, Canny-SVM, Sauvola-ANN, and Sauvola-SVM. The highest accuracy is achieved by the Sauvola-ANN method, with a value of 93.75%.

Keywords: ***ANN, citrus leaves, Canny, classification, Sauvola, SVM***

1. INTRODUCTION

In recent years, precision agriculture has emerged as a crucial approach to optimize crop production and address the challenges posed by global food security. The health and vitality of citrus trees, being a vital component of agricultural ecosystems, show a essential part in determining the yield and quality of citrus fruits. However, nutrient deficiencies in citrus trees can adversely affect their growth and overall health, leading to reduced productivity and economic losses for farmers.

Nutrients are elements that are essential for a plant's growth and reproduction. Macronutrients, which include potassium (K), phosphorus (P), nitrogen (N), sulfur (S), calcium (Ca), and magnesium (Mg), are often-used nutrients to identify plant nutrients. Nutrient intake is a significant factor in cultivating citrus [1]. Symptoms of plant nutrient shortage are often obvious in leaves and fruits, as seen in Figure 1. Deficiency symptoms are commonly utilised in citrus leaves to determine nutrient response. Currently, human inspectors are responsible for inspecting plants, but due to Indonesia's large volume of citrus production, these inspections tend to be error-prone due to fatigue. Accurate plant inspection requires highly skilled and experienced farmers and can be time-consuming and costly. Many farmers have low levels of education, making it difficult to implement complex technology on agricultural land. Therefore, farmers need a system with automated techniques that farmers can quickly adopt.

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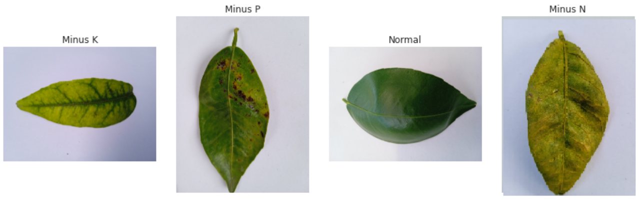

Figure 1. Comparison of citrus leaves for nutrient deficiencies syndrome

Traditional methods of nutrient deficiency assessment in citrus trees often involve manual inspection by experts, which can be time-consuming and prone to subjective judgments. With advancements in computer vision and machine learning technologies, there has been a growing interest in automating this process using leaf image analysis. Leaf images provide valuable visual cues related to the health status of citrus trees, and the use of artificial intelligence (AI) techniques can offer a more efficient and accurate approach for nutrient deficiency classification [2].

Previous research has focused more on detecting and classifying types of diseases, while nutrient deficiency is often the origin basis of plant diseases. Addressing nutrient deficiencies in plants can make them stronger and better able to withstand diseases. Previous studies on nutrient-level classification techniques have only classified nutrients as insufficient or sufficient without identifying which specific nutrient is deficient. Research on recognising nutritional deficits in plants using image processing techniques has yet to be significantly explored, as most research focuses on classifying plant diseases.

Traditional methods for determining plant nutrient content include plant analysis and tissue testing. These procedures are time-consuming, damaging, and need the collection of test materials. Non-destructive testing procedures are becoming increasingly popular since the benefits do not harm plants. SPAD meters are fairly easy-to-use but expensive tools. Research by [3] proposed a portable device based on sensors to monitor Nitrogen conditions in agricultural land. It's research has only in Nitrogen condition, not yet for other elements.

Image processing techniques can improve farming practices and management by increasing the accuracy of farmers' observations while reducing manual monitoring by farmers. Image processing techniques also provide flexibility and effectively replace farmers' visual decision-making [4]. The overall goal of image processing for scientific applications is to make use of the radiation generated by the object of observation. The imaging system gathers radiation to create pictures. Then, image processing techniques are employed to assess the object's similarity, wide area, and edge detection [5].

Steps must be taken to address plant nutrient deficiencies to minimise losses at harvest and avoid excessive use of fungicides. Many auxiliary technologies have been created to automate the image processing data and information. This technology's design and execution will substantially benefit in minimising the usage of chemical fertilisers, lowering prices, and improving output. Plant nutrition condition recognition is a new and attractive research area, however there are several hurdles to overcome when using image processing technology and learning algorithms to nutrition recognition in plants. Because erroneous detection might harm agricultural yield, the suggested algorithms must be extremely precise and have a limited margin of error.

Intelligent classification systems research is a comprehensive field that covers many separate tasks, such as data preprocessing, segmentation, feature extraction, classifier learning, etc. One of the most interesting problems is image recognition. Image processing techniques have significant applications in the analysis of smart farm technologies. A detection and classification system using digital image processing technology would be able to more accurately and quickly classify nutrient deficiency symptoms in citrus trees than a human eye could. It would enable farmers to take appropriate corrective action in farm management. The prime goal of this proposed research is to develop detection and classification methods for nutrient deficiencies in citrus leaves using image analysis techniques. The goal is to identify and quantify the colour and texture attributes of citrus leaves using the following stages:

- Image acquisition
- Image segmentation
- Feature extraction
- Image classification using ANN and SVM

The outcomes of this study not only contribute to the advancement of agricultural practices by providing a robust method for nutrient deficiency detection but also shed light on the strengths and limitations of ANN and SVM in this specific application. The results can guide agricultural experts and researchers in choosing the most suitable algorithm for similar tasks in precision agriculture, thus fostering sustainable and efficient crop management practices. Overall, the findings presented in this paper contribute to the emerging field of agricultural AI and hold promising implications for enhancing citrus tree health monitoring, crop yield optimization, and ultimately, global food security.

2. RELATED WORK

The segmentation process is characteristically determined by a previous on the solution space and the underlying data useful when the images contain objects with limitations in the image acquisition or corrupted [6]. The most frequently used discontinuity-based edge detection techniques are Sobel, Prewitt, Kirsh, Robinson, Marr-Hildreth, Roberts, LoG, and Canny Edge Detection. The Canny technique outperforms all other algorithms for a given picture because the different edge detections in Canny detection operate better under different situations. Sobel edge detection has a high processing speed but low precision, whereas Canny detection has a lower processing speed but excellent precision [7].

Features related to image sections. Objects in an image have a series of features that can be used to characterise images. The image recognition problem task isolates parts of the image that might contain the object/feature, measures features, and determines the most useful value in characterising it [8]. There are millions of colours involved in most images, differing in grey level images which only have the value 256, which is usually found. It means that thresholds and other calculations require careful calculations [9]. The HSV colour space is particularly effective and uses the most comparable photos for colour extraction, which increases the speed of the search system. The hue element is more prevalent than the saturation/value component in the HSV colour space, which is extremely similar to human visual perception. As a result, the extraction of HSV colour characteristics is superior than that of other colour spaces [10]. The GLCM approach characterises texture by generating statistics on the dispersion of intensity values as well as the location and orientation of related pixels, hence it outperforms other methods for texture feature extraction [11].

The classification problem is related to the analysis of the feature space structure. An object is considered a pattern in the feature space. The last stage in the pattern recognition challenge is image classification. In supervised classification, there is a priori knowledge about the picture to be categorised. ANN and Fuzzy Logic are the most common techniques used in the classification system. The other methods used in Logistic Regression (LR), Backpropagation Neural Networks, Deep Convolutional Neural Networks, etc. [12].

The researchers use Red, Green, and Blue (RGB) colour and Sobel edge detection for leaf shape recognition, as well as ANN for the identification procedure, to create the application of nutritional differentiation identification in cucumber [13]. The accuracy of the classification is less than 71%. Another researcher has implemented the ANN classification based on the tomato leaves image using texture extraction, resulting in an accuracy of 88.27% [14]. According to Rahadiyan's research, including the leaf's colour, texture, and shape improves model accuracy. The best feature combination is determined by combining RGB, GLCM, Hu, and centroid distance. With a 0.002 learning rate and 300 epochs, the features merged into the upgraded data results offer the best performance with 89.70% accuracy. In the previous study, the MLP architecture was compared against a variety of machine learning methodologies.

Consequently, SVM delivers the best results, with 90.55% accuracy [15]. The RGB extraction approach of Hue, Saturation, and Value (HSV) is presented in Yuslena's research for a digital image processing system for maise leaf pictures. This study uses Support Vector Machine (SVM) as a classification method to classify its picture results. The suggested approach achieves an accuracy of 80% in detecting nutritional content in maise leaves [16].

This paper discussed the implementation of methods proposed by the author [17]. The study explores numerous visual image-based strategies for detecting nutrient deficits in plants. Image processing approaches include numerous phases: image acquisition, improvement, segmentation, and feature extraction. According to the findings, image processing technology may aid in developing farming automation to achieve the benefits of cheap cost, high accuracy and high efficiency. The report offered a novel approach in each image processing phase for detecting nutritional shortage as the basis for future research through analysis and debate. As a result, the research will aid in advancing agricultural automation equipment and systems with more intelligent methods.

3. RESEARCH METHODOLOGY

The study was conducted by the experimental method. Citrus reticulata trees are cultivated using the grafting/sticking bud system on the host plants. The parent plant is a local citrus plant that has strong root properties but has fruit that is not of high quality. Sticking is done when the height of the plant reaches + 50 cm. After the attachment process has succeeded, plant nutrition conditions will be treated. At the initial treatment of the sample, 40 citrus trees in the hydroponic system were given different treatments, namely:

a Nitrogen (N) conditions are deficient, with each condition consisting of 10 pots.
b Phosphor (P) conditions are deficient, with each condition consisting of 10 pots.
c Potassium (K) conditions are deficient, with each condition consisting of 10 pots.
d Normal conditions consist of 10 pots.

Hydroponic systems are popular because they make fertiliser solution management easier and offer an acceptable supply of mineral elements in soluble form. Hydroponics is great for determining the correct nutrient concentrations for plants and researching the consequences of nutrient lack [18].

For data collection, the 6 oldest leaves perfectly developed from each tree were taken 8 months after giving nutrition to get the average yield. Each leaf was taken using a 16 MP smartphone camera 5 times so that there would be 1200 image files. The images are split into 2 partitions, i.e. 20 % testing sample and 80% training sample. so it will be 960 image files for training samples and 240 for testing samples. The files will be saved for the image processing phases. The image was captured using the RGB cameras in the smartphone with a 12M pixel camera. Then the image will store in a JPEG file.

To define the image quality, the Peak Signal to Noise Ratio (PSNR) is utilized. As a result, PSNR is computed and compared here. The higher the PSNR, the better the visual quality. PSNR is a key measurement parameter that serves as an evaluation criterion for reconstructed image quality. PSNR is expressed in decibels (dB) and is calculated as follows [19]:

$$PSNR = 20x\log_{10}\frac{255}{RMSE} \quad (1)$$

The value 255 is maximum possible value that can be achieved by the image signal.

SSIM is a parameter that is used to evaluate results using quantitative metrics. SSIM is calculated by dividing the original image by a distorted image, which is then turned into a vector. Using the following equation [20]:

$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (2)$$

Where,

μ_x = average value of X
μ_y = average value of Y
σ_{xy} = correlation coefficient on X and Y
σ_x^2 = difference in values on X
σ_{xy}^2 = difference in values on Y
$c_1 and c_2$ = two variables that stabilize the low denominator

For the detection procedure, the suggested research employs Canny edge detection and Sauvola's approaches. The ability to reduce noise before executing edge detection computations is a benefit of Canny edge detection. Sauvola's approach is one of the new threshold methods that have been adjusted in the notion of integral picture to meet the Otsu method's computing speed.

This research proposes using Grey Level Co-occurrence Matrix GLCM) texture characteristics combined with the global colour histogram methods for extracting colour features. The colour feature is an easily understood feature image's and most sensitive. Colour Feature values are obtained by statistical calculations such as mean, variance, skewness and entropy. A GLCM matrix is parametric for texture extraction with the 2D image presented in each image, and the stylistic features are the average of the matrix using the neighbourhood of distance d = 1 to the directions 0_0,45^0,90^0 and 135^0. It is because blemishes have no specific direction.

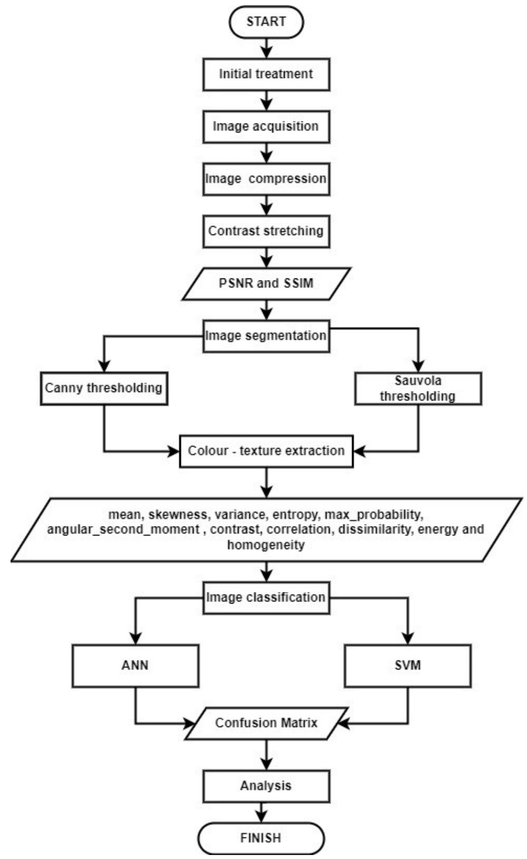

Figure 2. Research methodology flowchart

There are 7 features of GLCM used in this study, namely energy, correlation, contrast, entropy, dissimilarity, homogeneity, and maximum probability. These features and colour parameter's i.e., mean, skewness and variance used for classifying the image. After extraction, the data are prepared to be classified using the classification algorithm. The SVM and ANN classifications will be used distinctly. The classification output uses a confusion matrix to calculate the system's accuracy. The overall process is shown in Figure 2.

4. RESULTS AND ANALYSIS

The initial process of image processing begins with several stages, namely:

a Image compression
b image enhancement with contrast stretching
c Image segmentation by converting RGB image to HSV, then comparing 2 thresholding methods: edge-based thresholding (Canny detection) and threshold-based segmentation (Savuola Technique).
d Feature Extraction using colours and textures from HSV images

A. *Image Compression*

The Red Mi Note 9A smartphone camera captured images of leaves in the field and the specifications. The main camera of the Redmi 9A is 13 MP with a 2.2 mm lens opening and is a wide lens type, and has been equipped with an HDR feature. This camera can shoot images clearly and sharply. The 13 MP camera of the Redmi 9A is also equipped with Led Flash and HDR features to be used even in low light. The LED Flash feature will provide additional light for the camera so that the image results look better. In addition, HDR also plays an active role in adjusting the light balance.

As seen in Figure 1., the images have different positions. Some are in a vertical position (portrait), while others are in a horizontal position (landscape). The image transpose method is performed to align the positions. Flipping an image along its diagonal axis, thereby interchanging its rows and columns, is called image transposition. Depending on the implementation, this operation causes the image to rotate 90 degrees counterclockwise or clockwise. In Layman's terms, image transposition swaps an image's width and height, changing its orientation. This transformation is frequently used to align images of varying orientations or to prepare data for certain processing activities that necessitate a uniform image orientation. The process successfully transposes 129 vertical images to a horizontal orientation.

The next step after image transposition is to compress the image. It is done to reduce the size of the image. The method used is the lossless compression method. The lossless compression method in image processing has several advantages. When an image is compressed by a lossless method, the image returned after decompression is identical to the original image. With this method, there is also no loss of data or image quality [21]. The process output presents the file size before and after compression, as shown in Figure 3.

```
Iterating images: 395 / 395 [02:14,  2.93 / 395/s]
Total size before compression: 850.89 MB
Total size after compression: 25.59 MB
Percentage reduction in size: 96.99%
```

Figure 3. Research methodology flowchart

B. *Image Enhancement with Contrast Stretching*

The purpose of enhancing an image by contrast stretching is to increase the difference between the pixel intensity values in the image. As shown at Figure 4, Before the contrast stretching process, an image may have a limited range of intensities, meaning that pixels in the image might be concentrated in a narrow range of intensity values. As a result, the image appear dull or lackluster and look too dark with limited details.

Figure 4. Preview image before and after Contrast Stretching

After applying the contrast stretching process to the image, the intensity range is expanded. This is achieved by determining the minimum and maximum intensity values in the original image and then mapping these values to a wider intensity range, 0 to 255 for an 8-bit image. In this way, the pixel intensities, which were previously concentrated, are spread out more evenly across the entire range, and the intensity differences between pixels are enhanced. After the contrast stretching process, the image will appear sharper, with increased details in both objects and the background. Dark areas will become darker, and bright areas will become brighter, resulting in an overall increase in contrast. The outcome is a clearer image with more visible details, making it easier to analyze or interpret.

Both algorithms' performance was evaluated using two parameters, PSNR and SSIM. The additional code was introduced to the algorithm coding to measure the PSNR and SSIM values. These parameters were calculated and assessed to determine efficacy, and results were compared for both approaches to determine whether the algorithm performed significantly better for image enhancement.

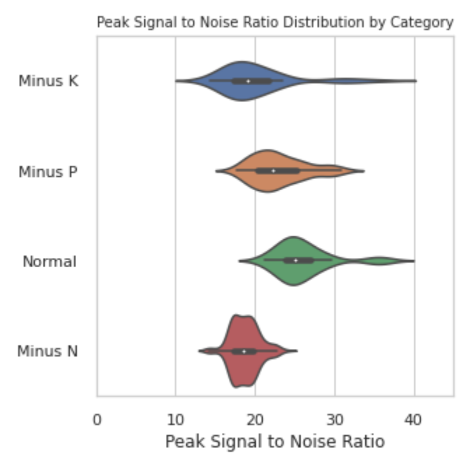

Figure 5. PSNR distribution by category

Parameters such as PSNR and SSIM are measured as shown at Figure 5. The maximum PSNR is 35.80, and the minimum PSNR is 14.01, with a good range of 25-30 dB for PSNR. The SSIM scores after compression and contrast stretching are 0.97 (maximum) and 0.88 (minimum), which fall within the good range of 0.8-0.9.

A histogram visualisation of the image samples is performed to analyse the images before and after the compression and contrast stretching process. A better histogram will show a more even distribution across the range of pixel values. Figure 6 shows an increase in the number of pixels in a wider contrast range; this means that the image resulting from contrast stretching has better contrast visually. the histogram shows a more even spread or significant increase in the range of pixel values above 200, indicating a successful contrast enhancement.

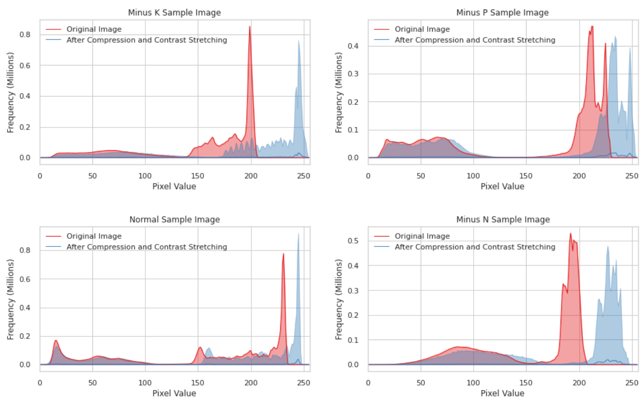

Figure 6. Histogram visualisation of the image

C. The Image Segmentation of Image Using Canny And Sauvola's Methods

In the segmentation process, the sample image will be converted into multiple channels from different colour spaces to determine which channel can provide significant pixel differences, making the segmentation process easier. The RGB images convert to HSV colour spaces. For Canny edge thresholding, the saturation channel from the HSV colour space is chosen due to its distinct intensity differences between the foreground and background, making edge detection more accurate. For Sauvola thresholding, the blue channel from the RGB colour space is used because the available image data contains a minimal amount of blue, which makes the blue channel less affected by noise.

Image results with the Canny method are dominated by sharp and smooth edges, as shown in Figure 7 and Figure 8. The Canny algorithm effectively identifies edges in images with high precision so that the resulting edges tend to be sharp and clear. Canny's method also applies noise removal before edge detection is performed. Therefore, the image results from the Canny method are free from noise interference and provide more accurate edges. But the drawback is that the image results of the Canny method look very precise on edge detection, so some parts of the image are considered edges.

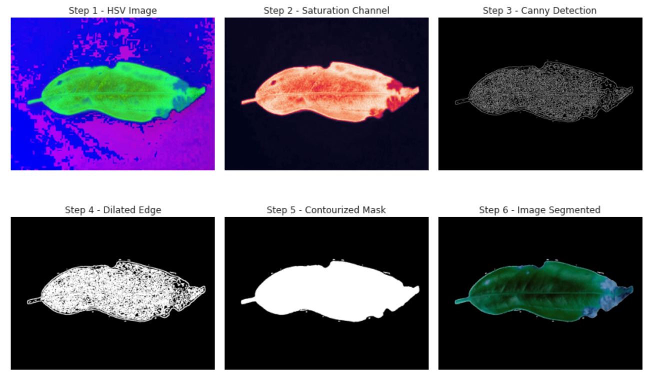

Figure 7. Result of steps in Canny Edge Thresholding Process

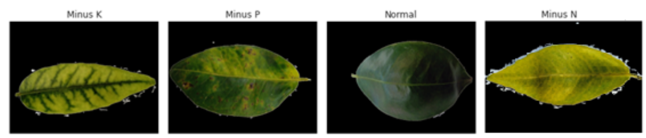

Figure 8. Preview for each deficiency category on Canny segmented

Image results with the Sauvola method usually have an increase in local contrast. As shown in Figure 9, areas that were initially too dark or had low contrast tend to become lighter and have better contrast after this process. The Sauvola method retains details in the image, as shown in Figure 9 and Figure 10. The fine features and textures in the image tend to be well preserved after applying this method. In this study, texture and colour feature extraction will be carried out so that Sauvola produces a better image because it produces a clearer image. If feature extraction is done based on area, the Canny method is a better alternative than the Savuola method. If the data is an image with sharp edges, then the Canny method will be better at detecting the edges of the image. However, if the existing data is an image with a large variation of lighting, the Sauvola method can be more useful.

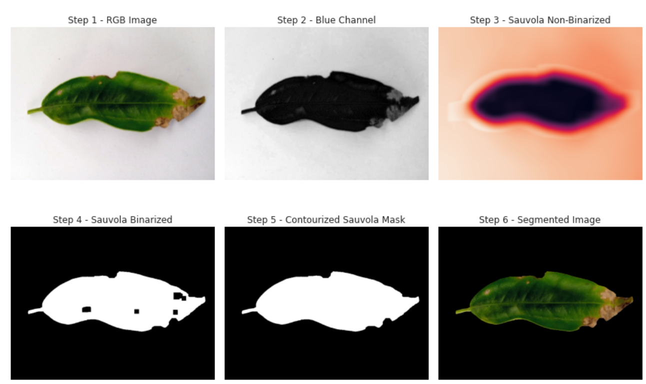

Figure 9. Preview of Sauvola Thresholding Process

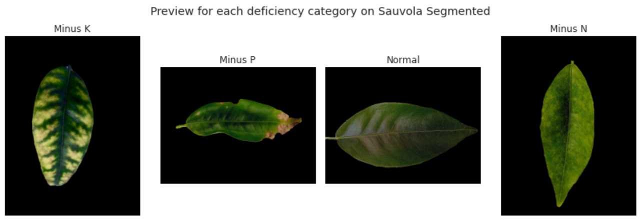

Figure 10. Preview for each deficiency category on Savuola segmented

The research includes a feature analysis section to investigate the extracted features from the colour-texture extraction process. Specifically, the aim is to identify whether each deficiency category exhibits unique variables that can differentiate it from others. The feature analysis aims to determine the separability of the variables within and between categories. The results of this analysis will provide insights into the informativeness and relevance of the extracted features and their potential for building accurate and reliable models for classification [22]. Visualisation for feature analysis in this section uses the Shapiro Ranking Algorithm, which is based on the Shapiro-Wilk test. The Shapiro-Wilk test is a statistical method used to test the normality assumption in data samples. As seen in Figure 11, the value of each parameter in the colour-texture feature is close to 1. It shows that the data are normal.

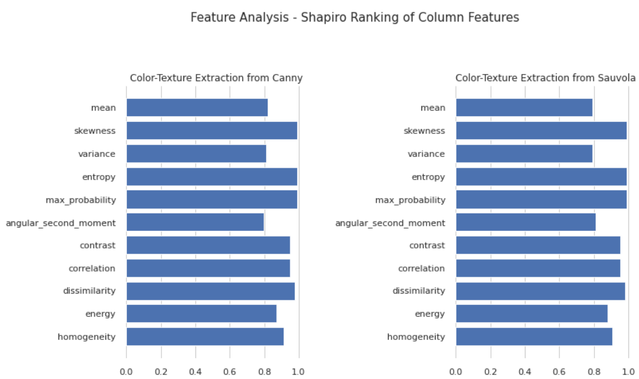

Figure 11. Feature Analysis Shapiro Ranking of column features

The mean, skewness, and variance for each H, S, and V channel are then calculated. The mean is a statistical metric that describes the distribution's central tendency. Skewness is a statistical measure of asymmetry or lack of symmetry in a probability distribution. It provides information about the shape of the distribution of a dataset. Variance calculates the average squared deviation of each data point from the mean.

The next step is to perform feature extraction using the GLCM method. The grey-level co-occurrence matrix (GLCM) is a statistical representation of the relationship between pixel intensities in an image. GLCM features can provide information about spatial patterns and correlations among neighbouring pixel values. In this case, GLCM features are calculated considering specific angles (0, 45, 90, and 135 degrees in radians) and specified distances.

The combination of colour and texture feature extraction produces parameters mean, skewness, variance, entropy, max_probability, angular_second_moment, contrast, correlation, dissimilarity, energy and homogeneity as shown at Figure 12.

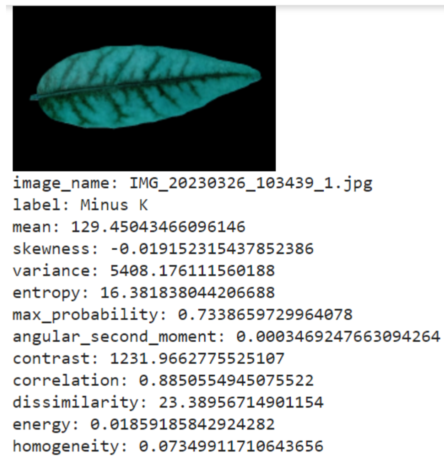

Figure 12. Colour-Texture extraction output sample

D. Classification using ANN

The training and test data will be split with 80:20 proportion from the available 1200 data. Every 25 data iterations, the sequence 1-20 will become the training data, and the sequence 21-25 will become the test data, resulting in an 80:20 ratio for the training and test data.

Before carrying out the ANN process, determine the classification metrics that will be sought as a result of evaluating the ANN process. The parameters are:

a Accuracy Score; A classification metric that assesses the overall correctness or accuracy of a classification model's predictions is the accuracy score. A greater accuracy score implies better classification model performance and a higher level of correct predictions.

b Confusion Matrix; The confusion matrix is a tabular representation that summarises a classification model's performance by presenting the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions generated by the model.

The next process is Training the ANN model. These steps aim to build, train, and evaluate a neural network model for a multi-class classification task. The first step is initialising the neural network model and defining its structure. The model uses a sequential approach, meaning that layers of the neural network are added one after another. In this step, two layers are added to the model. The first layer, Dense (fully connected) with 16 units/neurons, uses the ReLU activation function. The second layer is another Dense layer with 4 units/neurons, using the softmax activation function typically used for multi-class classification. After constructing the model, the next step is to compile it. During this step, several parameters required for the model training process are defined, such as the optimiser to be used (Adam), the loss function (sparse_categorical_crossentropy as the labels are in integer format), and the evaluation metric (accuracy) to be used during training. With the model defined and compiled, the next step is to train the model using the training data. The training is performed for 75 epochs, meaning the entire training dataset will be presented to the model 75 times.

The output of the process is as follows:

```
------------------------------------------------
Training model ...
------------------------------------------------
Test Loss: 0.2534336745738983
Test Accuracy: 0.9333333373069763
--------
```

After training, the history is saved as a data frame for further analysis and visualisation. The training history includes information such as loss and accuracy at each epoch. ANN model architecture is shown in Figure 13.

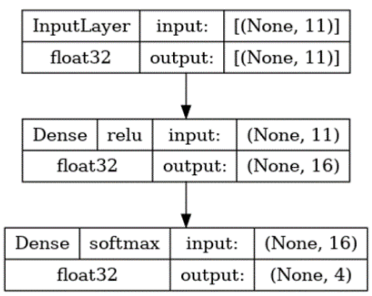

Figure 13. ANN Model Architecture from Canny and Sauvola Segmented Image

The output process of the training data is as follows:

```
ANN Classification with Color-Texture Extraction
from Canny Segmented Image
================================================
Accuracy score: 0.9333333373069763

Classification Report:
              Precision recall  f1-score
support

     Minus K  0.93      0.95      0.94        60
     Minus N  0.95      0.87      0.90        60
     Minus P  0.90      0.95      0.93        60
     Normal   0.95      0.97      0.96        60

    accuracy                      0.93       240
   macro avg  0.93      0.93      0.93       240
weighted avg  0.93      0.93      0.93       240

Confusion Matrix:
[[57  2  0  1]
 [ 3 52  5  0]
 [ 0  1 57  2]
 [ 1  0  1 58]]
```

Accuracy is the most commonly used parameter to judge the machine learning model. The model has an output of 89.17% accuracy. Sensitivity or recall is the ratio of the TP to the number of actual good outcomes. The recall is calculated using the formula TP/(TP+FN). This parameter evaluates the ML model's ability to analyse the input and identify the real outcome. The lowest recall value in this segment is the value for P-Minus 75%. The F1 score is the harmonic mean of accuracy and recall. It is utilised as an overall metric that considers accuracy and recall. On an unbalanced dataset, these harmonic mean analyses false positives and negatives. The F1-Score value has a good score indicating that our classification model has good precision and recall.

Based on Figure 14., 60 training data are processed. The confusion matrix results show that 57 K-minus images have a good agreement between the predictions and the original data. 2 images that should be imaged with K-minus are considered N-minus images, and 1 image is considered normal. 56 N-minus images have a similar result between the predictions and the original data.3 images that should be imaged with N-minus are considered K-minus images, and 1 is considered a P-minus image. 45 P-minus images have similar results between the predictions and the original data.10 images that should be imaged with P-minus are considered N-minus images, 3 are K-minus, and 2 are considered Normal images. 56 Normal images have similar results between the predictions and the original data, and 4 images that should be imaged under normal conditions are considered K-minus images.

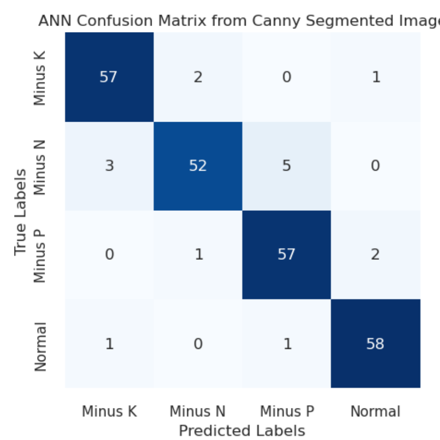

Figure 14. ANN Confusion matrix from Canny Segmented image

The next step is building the ANN model using Sauvola segmented image. The model has output 93,07% in accuracy. The lowest value of recall in this segment is the value for N-Minus 87%. The F1 score is the harmonic mean of accuracy and recall. It is utilized as an overall metric that takes accuracy and recall into account. On an unbalanced dataset, these harmonic mean analyses both false positives and false negatives. The F1-Score value more than 0.90 has a good score indicating that the classification model has good precision and recall.

The overall output is the following:

```
ANN Classification with Color-Texture Extraction
from Sauvola Segmented Image
==================================================
======================

Accuracy score: 0.9375

Classification Report:
            Precision recall  f1-score   support
Minus K        0.95      0.95      0.95        60
Minus N        0.95      0.87      0.90        60
Minus P        0.90      0.95      0.93        60
Normal         0.95      0.98      0.97        60

accuracy                           0.94       240
macro avg      0.94      0.94      0.94       240
weighted avg   0.94      0.94      0.94       240

Confusion Matrix:
[[57  2  0  1]
 [ 3 52  5  0]
 [ 0  1 57  2]
 [ 0  0  1 59]]
```

Based on Figure 15, 60 training data are processed. The confusion matrix results show that 58 K-minus images have a good agreement between the predictions and the original data. 1 image that should be imaged with K-minus is considered an N-minus image, and 1 is a normal image. 50 N-minus images have similar results between the predictions and the original data. 5 images that should be imaged with N-minus are considered K-minus images, and 5 are considered P-minus images. 43 P-minus images have similar results between the predictions and the original data. 12 images that should be imaged with P-minus are considered N-minus images, 1 image is considered K-minus, and 4 images is considered Normal image. 58 Normal images have similar results between the predictions and the original data, and 2 images that should be imaged under normal conditions are considered K-minus images.

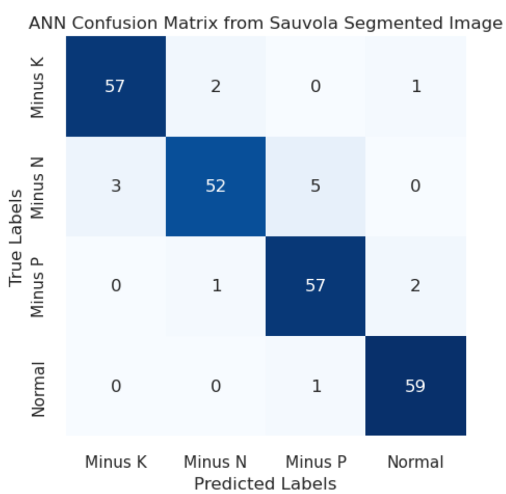

Figure 15. ANN Confusion matrix from Sauvola Segmented image

E. *Classification using SVM*

The SVM algorithm begins with the retrieved pictures from the previous phase. The information will be separated into training and testing data. SVM seeks the optimum hyperplane in the input space. SVM is a linear classifier at its core, but it was further refined to operate on non-linear situations by including the kernel trick notion in a high-dimensional workspace. The core process of SVM is finding the hyperplane that separates the data with the maximum margin. This involves transforming data into higher dimensions using the kernel, selecting support vectors, and optimizing margins. The goal is to produce a strong and effective classification model.

As the results, shown in Figure 16., 60 training data are processed. the results of the confusion matrix show that 59 K-minus images have a good agreement between the predictions and the original data. 1 image that should be imaged with K-minus is considered a normal image. 55 N-minus images have a similar result between the predictions and the original data. 2 images that should be imaged with N-minus are considered K-minus images, and 3 images are considered P-minus images. 51 P-minus images have a similar result between the predictions and the original data. 7 images that should be imaged with P-minus are considered N-minus images, and 2 images are considered Normal images. 59 Normal images have similar results between the predictions and the original data, and 1 image that should be an image under normal conditions is considered a K-minus image.

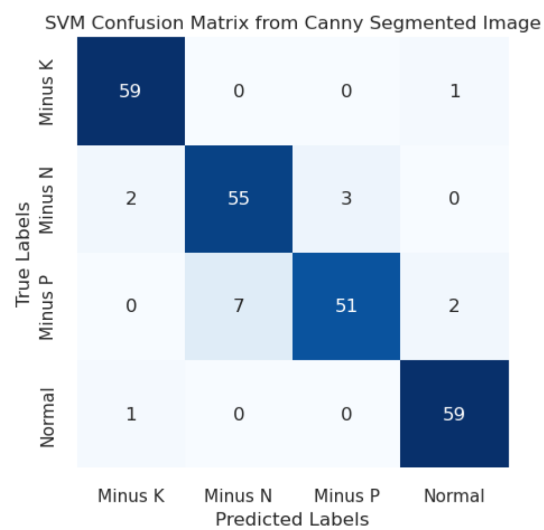

Figure 16. SVM confusion matrix from Canny segmented image

The model has accuracy 93,3%. It results in better accuracy according to the ANN model from Canny segmented image. The accuracy metric represents the overall correctness of the model's predictions. In this case, the accuracy is reported as 0.93, which means the model achieved 93% accuracy in its predictions. The macro average for precision, recall, and F1-score is reported as 0.93. The weighted average for precision, recall, and F1-score is reported as 0.93. Since all the metrics—accuracy, macro average, and weighted average—are reported as 0.93, it indicates that the model performed consistently well across the evaluation metrics and achieved an overall accuracy of 93% in its predictions.

The results accuracy is:

```
SVM Classification with Color-Texture
Extraction from Canny Segmented Image
===========================================
============================

Accuracy score: 0.9333333333333333

Classification Report:
         Precision recall  f1-score   support

Minus K  0.95    0.98      0.97      60
Minus N  0.89    0.92      0.90      60
Minus P  0.94    0.85      0.89      60
Normal   0.95    0.98      0.97      60

accuracy                     0.93        240
macro avg     0.93   0.93    0.93        240
weighted avg 0.93    0.93    0.93        240

Confusion Matrix:
[[59  0  0  1]
 [ 2 55  3  0]
 [ 0  7 51  2]
 [ 1  0  0 59]]
```

The next process is the classification of the Sauvola segmented data using SVM. The results shown in Figure 17, 60 training data are processed. The confusion matrix results show that 57 K-minus images have a good agreement between the predictions and the original data. 1 image that should be imaged with K-minus is considered a normal image. 1 image was predicted as a P-minus image, and 1 was an N-image. 52 N-minus images have similar results between the predictions and the original data. 3 images that should be imaged with N-minus are considered K-minus images, and 5 are considered P-minus images. 54 P-minus images have similar results between the predictions and the original data. 3 images that should be imaged with P-minus are considered N-minus images, 2 are considered Normal images and 1 image is predicted as a K-minus image. 59 Normal images have similar results between the predictions and the original data, and 1 image that should be an image under normal conditions is considered a P-minus image.

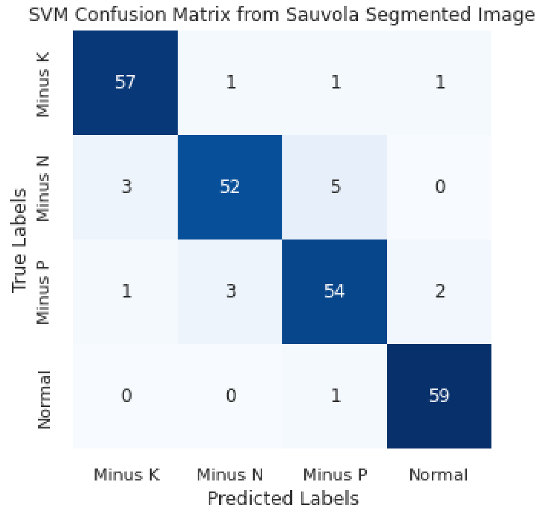

Figure 17. SVM confusion matrix from Sauvola segmented image

The results accuracy is:

```
SVM Classification with Color-Texture
Extraction from Sauvola Segmented Image
===========================================
============================

Accuracy score:
0.9367088607594937Classification report:
    Precision recall  f1-score   support

Minus K  1.00     0.70      0.82         10
Minus N  0.95     1.00      0.97         38
Minus P  0.86     0.95      0.90         20
Normal   1.00     0.91      0.95         11

accuracy                         0.94        79
macro avg     0.95      0.89     0.91        79
weighted avg  0.94      0.94     0.93        79

Confusion Matrix:
[[ 7  1  2  0]
 [ 0 38  0  0]
 [ 0  1 19  0]
 [ 0  0  1 10]]
```

The classification system for nutritional deficiencies in citrus plants based on the images of the leaves has been completed. Overall, there are 4 data obtained:

1’ Image data is segmented using the Canny method and classified using ANN (C-ANN).
2. Image data is segmented using the Sauvola method and classified using ANN (S-ANN).
3. Image data is segmented using the Canny method and classified using SVM (C-SVM).
4. Image data is segmented using the Sauvola method, classified using SVM (S-SVM)

TABLE I. COMPARISON PARAMETERS OF ANN AND SVM

Parameters	ANN		SVM	
	Canny	Sauvola	Canny	Sauvola
Accuracy Score	0.8917	0.9375	0.9333	0.9250
Classification Report				
Precision (Minus K)	0.85	0.95	0.95	0.93
Precision (Minus N)	0.82	0.95	0.89	0.93
Precision (Minus P)	0.98	0.90	0.94	0.89
Precision (Normal)	0.95	0.95	0.95	0.95
Recall (Minus K)	0.95	0.95	0.98	0.95
Recall (Minus N)	0.93	0.87	0.92	0.87
Recall (Minus P)	0.75	0.95	0.85	0.90
Recall (Normal)	0.93	0.98	0.98	0.98
F1-score (Minus K)	0.90	0.95	0.97	0.94
F1-score (Minus N)	0.87	0.90	0.90	0.90
F1-score (Minus P)	0.85	0.93	0.89	0.89
F1-score (Normal)	0.94	0.97	0.97	0.97
Confusion Matrix				
Minus K vs. Minus K	**57**	**57**	**59**	**57**
Minus K vs. Minus N	2	2	0	1
Minus K vs. Minus P	0	0	0	1
Minus K vs. Normal	1	1	1	1
Minus N vs. Minus K	3	3	2	3
Minus N vs. Minus N	**56**	**52**	**55**	**52**
Minus N vs. Minus P	1	5	3	5
Minus N vs. Normal	0	0	0	0
Minus P vs. Minus K	3	0	0	1
Minus P vs. Minus N	10	1	7	3
Minus P vs. Minus P	**45**	**57**	**51**	**54**
Minus P vs. Normal	2	2	2	2
Normal vs. Minus K	4	0	1	0
Normal vs. Minus N	0	0	0	0
Normal vs. Minus P	0	1	0	1
Normal vs. Normal	56	59	59	59

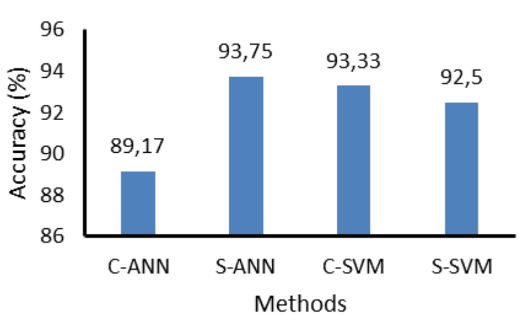

Figure 18. comparison of the accuracy of each method

As shown in Table 1 and Figure 18, the classification of nutritional deficiencies using ANN with data from the Sauvola segmentation method has a higher accuracy rate of 93.75%. In contrast to the SVM classification method, the highest accuracy is obtained from the Canny segmentation method, with 93.33%. The highest accuracy value is obtained through the ANN classification method from image segmentation data using the Sauvola method, which is 93.75%.

The Sauvola method has produced better leaf image segmentation than other segmentation methods. Good segmentation ensures that the important features of the leaf are well isolated and used by the classification model. With accurate segmentation, ANN can access relevant leaf features, improving overall classification performance. The Sauvola method has identified leaf features that are more relevant and significant for classifying nutrient deficiencies in citrus trees. These features help the ANN methods to understand the differences between different classes of nutritional deficiencies better, thereby increasing the classification accuracy. Artificial neural networks (ANN) can recognise complex patterns in data. Suppose the processed data has been properly segmented and the appropriate features have been extracted. In that case, ANN can ”learn” these patterns and adjust its model parameters to achieve high accuracy in classification.

The lowest accuracy value is obtained from the classification process using ANN from segmentation data using the Canny method, which is 89.17%. The Canny method is an edge detection algorithm that can provide segmentation results with sharp and accurate edges. However, in some cases, more than the segmentation results by Canny may be required for the task of classifying nutrient deficiencies in citrus trees. The segmented image may contain noise or have edge detection errors, which can interfere with the feature extraction process and reduce classification accuracy. The Canny method produces edges in the image, but this process can lead to the loss of some relevant feature information on the leaves. As a result, the ANN may not access the essential features needed to classify nutritional deficiencies properly. ANNs can have different levels of abstraction depending on the features extracted from the image, and the Canny method may not produce features that match the level of abstraction required by ANNs for this complex classification task. As a result, the ANN may not recognise the patterns necessary to classify nutritional deficiencies with high accuracy.

Weaknesses in the ANN and SVM methods can be corrected using optimisation methods. Optimisation methods play a central role in improving the performance and efficiency of training ANN and SVM. In the context of ANN and SVM, optimisation methods are used to find the optimal model parameters, enabling the model to achieve the best accuracy and performance in classification, regression, and other modelling tasks. Additionally, optimisation methods help address overfitting by controlling model complexity, preventing the model from memorising training data and enhancing its ability to generalise to unseen test data. The appropriate optimisation methods can also speed up model convergence, saving training time and reducing computational burden. Furthermore, optimisation methods assist in navigating the vast parameter space and adapting the model to changing data over time. We can develop more reliable, efficient, and better-generalising ANN and SVM models for unseen data by effectively leveraging optimisation methods.

This study's classification of nutritional deficiencies is based only on the image of citrus leaves that have gone through the hydroponic treatment stage for 8 months. This condition will be different from the real results obtained in the agricultural field because citrus trees are plants that can grow up to 10 years. In addition, it is necessary to add parameters other than texture and colour, such as leaf size and the same age. There is a possibility that the appearance of colour and texture on citrus leaves is also caused by disease in plants, so it is necessary to develop a classification system that integrates nutritional deficiencies and diseases in citrus plants.

5. CONCLUSION AND FUTURE STUDIES

In this research, image processing was carried out using two segmentation methods: Canny and Sauvola. Canny segmentation is an edge detection algorithm that produces sharp edges in images. The Sauvola method is an adaptive filter-based segmentation method that produces better segmentation in citrus leaf images. Apart from Canny and Sauvola, many other segmentation methods can be explored to compare performance and choose a more suitable method for classifying nutritional deficiencies in citrus leaves. For example, deep learning-based segmentation methods such as U-Net or Mask R-CNN can be explored.

This study also compared the performance of two classification methods, ANN and SVM, in classifying nutritional deficiencies in lime leaves after segmentation. The evaluation results revealed that the ANN model for data segmentation results of the Sauvola method provides higher accuracy than SVM for this classification task, which is equal to 93.75%. It is due to the adaptability of the ANN model in recognising complex patterns in the training data and its ability to access relevant features after Sauvola segmentation, contributing to better performance compared to SVM, with an accuracy score equal to 92,50%. Setting the parameters of the ANN and SVM models can significantly affect the model's performance. Applying optimisation techniques to find optimal parameters can help improve model performance.

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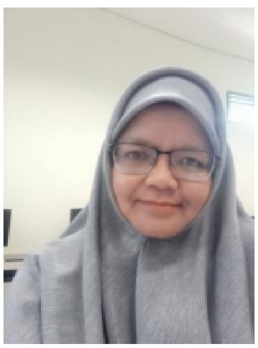

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