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Classification of Longan Types Using The Back-Propagation Neural Network Algorithm Based on Leaf Morphology With Shape Characteristics

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ABSTRACT

In Indonesia, longan fruit is abundantly accessible. The Longan fruit comes in a number of kinds, and they vary in terms of their morphology, including the characteristics of their leaves. The varieties of longan fruit are to be categorized in this study based on the shape of the leaves. The author uses the RGB color extraction function, the Grey Level Co-occurrence Matrix (GLCM), and the Shape feature to get data for each cultivar. The accuracy value is then processed using the Back-Propagation Neural Network (BPNN) technique to determine the accuracy value that will be used as a determinant of the categorization of the Longan leaf image. The eccentricity and metric parameters are key components of the method. The BPNN algorithm demonstrated its usefulness for categorizing various kinds of longan fruit leaves during testing by obtaining an accuracy of 70%.

Keywords: *Longan; Image Processing; RGB; GLCM; Shape, Back-Propagation Neural Network*

1. INTRODUCTION

In the archipelago, heterogeneous fruit plants are a natural resource for which we should be grateful. There may be multiple cultivars of a single fruit variety, each having unique traits. The longan, also known as the longan fruit, is one of the fruits with numerous cultivars. The longan fruit, or Dimocarpus longan in scientific terminology The lowlands of southwest India, the plains of China, and Burma are the origins of the fruit known as lor. [1]. On several cultivars of longan fruit, there are different variations in fruit size, fruit skin color, and leaf morphology. The longan fruit (Dimocarpus Longan Lour), which comes from a tropical fruit tree in the Sapindaceae family of soapberries, is a meaty, white fruit that tastes similar to lychee and is typically offered fresh, dried, or in soppiness in canned form. It is frequently cultivated because of its delectable flesh's sweet flavor. In the archipelago, two varieties of longans are grown: native longans and imported longans. Numerous cultivars of the local longan fruit exist, including kopyor- and stone-type longans. [2].

The authors carried out a study that concentrated on digital image processing techniques by using Longan leaves as the major object of research in order to be able to categorize the cultivars of Longan fruit. The research of feature extraction from leaves is difficult. Therefore, research in this area is interesting to look into. According to the definition of botanical science, numerous investigations have been conducted in the grouping of plants. [3]. It would be excellent to use image analysis and a form factor with complex dimensions to identify different leaf types. [4]. Research [5] explains that leaves are the main part of a plant, so the discussion of the development of control mechanisms for determining the shape of leaves becomes important for determining the type and condition of plants.

Digital image processing research on objects has received a lot of attention. The classification and identification of objects may be accomplished using a single method or a combination of several, according to some studies on digital image processing. The author employs a number of techniques to determine a value for each attribute and determine its accuracy rate. The use of the Grey Level Co-occurrence Matrix (GLCM) feature is one of them; this feature performs well in comparison to other features. [6]. Research [7] shows that the combination of GLCM, RGB, and Neural Network has a very good level of accuracy compared to using only one feature. Research [8] also shows excellent accuracy of the use of GLCM, i.e., showing texture descriptions that are more effective in recognizing patterns on an object. Research [9] about the classification of longan fruits based on leaf morphology using the Back- Propagation Network method produced a fairly good accuracy, namely 46,154. This level of accuracy is due to the lack of image detection features, so in this study, the authors added a combination of features to increase the accuracy rate.

In addition, the use of RGB features in the study [10] resulted in an average accuracy of 72% in identifying leaf types in plants. This accuracy is quite high, although the tools used in the data acquisition process are inadequate. The use of the shape feature in the study [11] resulted in an accuracy of 87.5% although some attributes cannot be used as a characterizer. This is because the attributes on the shape feature cannot identify certain characteristics if the distribution is evenly distributed. Research [12] indicates that the use of the GLCM feature can detect up to 90% of the classification of color textures. The selection of GLCM features in research [13] because this feature is not difficult to implement in detecting relationships between pixels.

The accuracy achieved in research to categorize fruit types using the BPNN approach utilizing the trainlm and traingdx models was good, reaching 100% in the case of the trainlm model and 96.05% in the case of the traingdx model [14].

Research [15] is related to leaf morphology, where leaf size plays an important role in influencing the final result. This served as the foundation for the idea that fruit classification can be determined based on the morphology of the leaves. It is also possible to successfully and with a reasonable degree of accuracy identify the type of fruit in other types of plants by their leaf shape [16].

The Back-Propagation Neural Network (BPNN) approach has been used successfully in a number of studies. The study [17] using BPNN obtained an accuracy of 98,82%. With learning rates of 0,7 and 0,9 for each iteration and 0,5, 0,7, and 0,9 for the 3000th iteration, this accuracy was achieved in the 2000th and 3000th iteration patterns. High precision, recall, and F-Measure values are also produced by this design. The application of BPNN in the study [18] obtained an accuracy of 88.75%, where this method succeeded in classifying using leaf morphology as a data object. The accuracy of the research employing the RGB, GLCM, and Form characteristics was fairly high. This shows that by employing the qualities of each feature extraction, colors, pixels, and forms on leaves can be recognized and categorized. This study uses the BPNN approach to categorize different cultivars of longan fruit according to the shape of their leaves.

2. RESEARCH METHODOLOGY

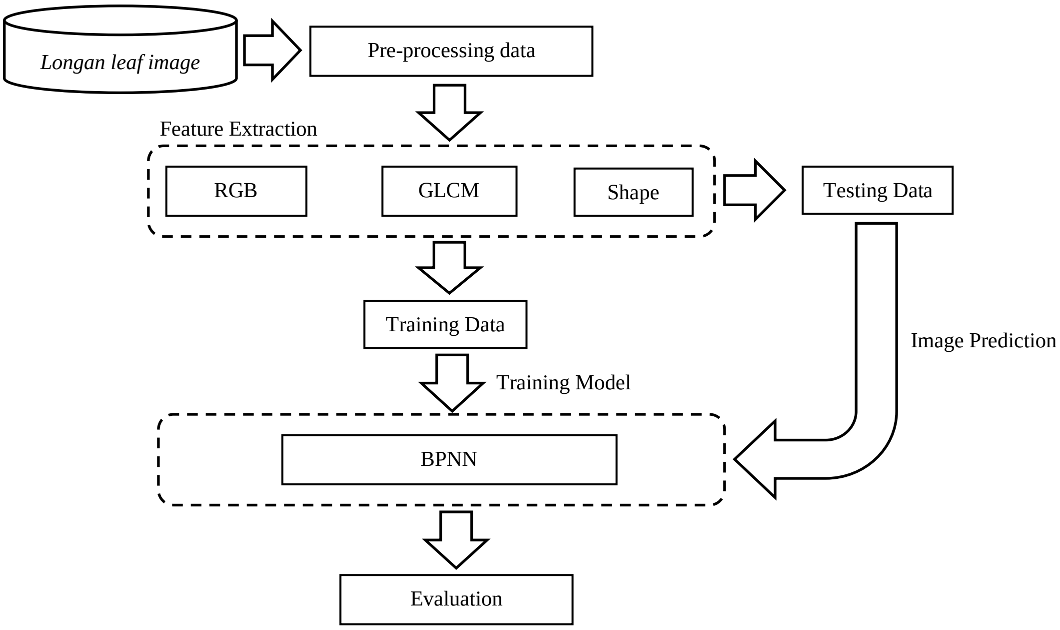
This study began by collecting data in the form of longan leaves from several trees using a dataset in the form of longan leaf images from 4 (four) different trees. The dataset of longan leaf imagery is then pre-processed by equalizing the image size and equalizing the image background. After that, images of each type are extracted with the RGB color feature, GLCM feature, and Shape feature. The score obtained is then used as input for the BPNN classification algorithm to predict the match value on each leaf-type image. Furthermore, the predicted results are evaluated by combining several types of extraction and separating them. This was done to ascertain how well the predicted results in this study were. This research was conducted using hardware with specifications; processor

AMD Ryzen 7, 16 GB RAM, 512 GB SSD. The software used is Microsoft Windows 11 operating system and Matlab R2021a application. The stages of the study are shown in Figure 1.

Figure 1 Step of the research

2.1 Data Collecting

The Semarang City Agricultural Extension Center (BPP) officials as well as skilled developers in the Semarang City region provide the direction for data collecting. Researchers have chosen to collect longan varieties that have been widely cultivated for both market fulfillment and collection plants. Researchers chose 4 (four) varieties of longans that may grow well. Itoh longan, Crystal longan, Red/Ruby longan, and Pimpong longan are the different



types of longans that are utilized.

Figure 2 Itoh

Figure 3 Kristal

Figure 4 Ruby

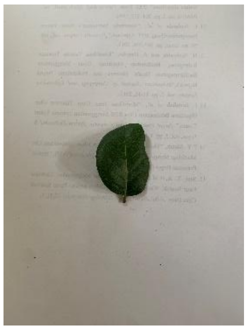


Figure 5 Pimpong

An object is placed on an empty field, and then an image of the object is taken from 30 cm away using a smartphone camera with a resolution of 12 megapixels. Here is an illustration of a top-notch leaf image for each tree.

2.2 Pre-processing Data

After getting the image of the longan leaves, data is first pre-processed with the intention of producing high-quality data processing. The size of the image and the image's background are equalized as part of the data's pre-processing. The image's dimensions are 433 by 577 pixels, and its background is single-color white.

2.3 Feature Extraction

After pre-processing the data, each image will be extracted using the RGB, GLCM, and Shapes features. Each feature will produce a value that becomes the input of testing and training so that the extraction results are used as training data and test data.

Each color has the primary spectral components of red, green, and blue according to RGB models (Red, Green, and Blue). The Cartesian coordinate system is used in this model. In Figure 7, a cube with the primary RGB values situated at three angles, cyan, magenta, and yellow located in the remaining three corners, black as the origin, and the void in the corner furthest from the origin, makes for a fascinating color subspace. A line connecting two points in this model's grayscale, which is a point with the same RGB value, goes from black to white. The various colors in this model are determined by a vector that extends from the end of the origin and corresponds to points on or inside the cube. It is assumed, for ease of use, that all color values have been normalized such that the cube depicted

Figure 6 Image with resolution 433 x 577 pixel

in Figure 7 is a unit cube. That is, it is assumed that all R, G, and B values fall inside the range [0, 1] in this representation. Keep in mind that the prefix RGB can be thought of as a unit vector that was derived from the cube's origin.

Three-component images—one for each primary color—are used to represent images that employ the RGB color paradigm. These three images are blended on the screen when placed into an RGB display to create a composite color image, as was mentioned in the preceding discussion. The number of bits used in a pixel serves as a measure of its depth. Think of an RGB image, where the red, green, and blue images are each an 8-bit image. Each RGB color pixel [a triplet of values (R, G, and B)] in this state has a density of up to 24 bits (3 image planes multiplied by the number of bits per field).

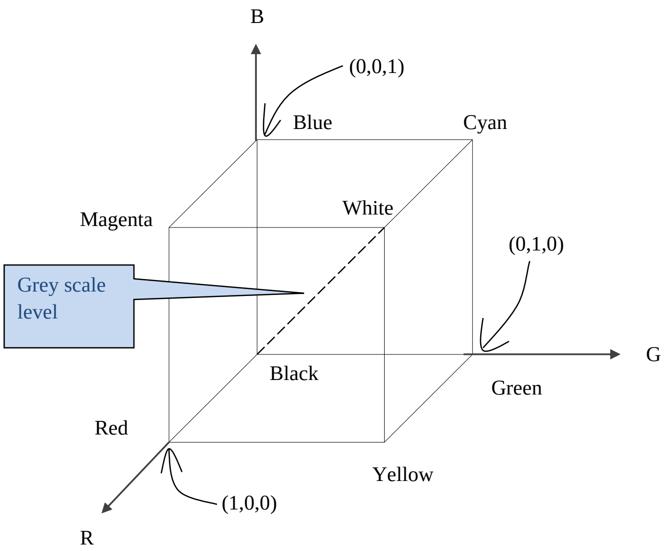


Figure 7 RGB cube scheme [20]

A 24-bit RGB color image is frequently referred to as a "full-color image." A 24-bit resolution RGB image can have (28)3 = 16,777,216 different colors. Figure 8 depicts a 24-bit RGB color cube that matches the illustration in Figure 7. Also keep in mind that with digital photos, the cube's range of values is scaled to the number that the image's bit count can represent. The edges of the cube along each axis become [0.255] if, like in the example above, the primary picture is an 8-bit image. When it happens, for instance, white will be at the cube's [255, 255, 255] point [19].

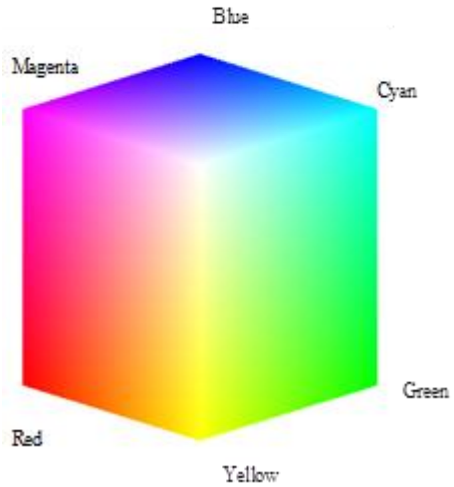


Figure 8 RGB cube 24-bit [20]

The use of the Grey Level Co-occurrence Matrix (GLCM) feature began in 1973 when Haralick proposed 28 features to explain space and place patterns. In the second order, GLCM uses texture as a reference for counter-values. Whereas in the first order, statistical calculations used for texture measurements that refer to the pixel value of the original image, such as variance, and the neighboring relationship of the pixels are not a concern. The relationship between the pairs of two pixels of the original image begins to be taken into account in the second order [20].

For example, $f(x, y)$ is a N_x and N_y sized image in which there are pixels with the most probability of L levels and $\vec{r}$ is the direction of vector displacement. $GLCM_{\vec{r}}(i, j)$ is defined as the number of pixels with the value $j \in 1, .., L$ coming out at offset $\vec{r}$ being pixels of value $i \in 1, .., L$, as expressed in the following equation (1):

$$GLCM_{\vec{r}}(i,j) = \#\{(x_1,y_1),(x_2,y_2) \in (N_x,N_y) \times (N_x,N_y) | f(x_1,y_1) = j^{\vec{r}} = \overrightarrow{(x_2 - x_1, y_2 - y_1)}\} \quad (1)$$

Under such conditions, the offset $\vec{r}$ represents the angle and/or distance. Figure 9 shows several GLCM directions. An object has characteristics associated with it. The shape feature is one of the features obtained based on the shape of the object and can be represented by contours, regions, and transformations, as shown in Figure 10. Shape features are usually represented by the contours, regions, and transformations of objects [20]. The calculation on the shape feature is based on metric and eccentricity variables. A calculation between the area and circumference of an object that can produce metric variables. While the calculation values of the focal distance of the major ellipse and the minor ellipse focus produce the eccentricity variable. The formula used to calculate the metric (2) and eccentricity (3) values is:

$$e = \sqrt{1 - \frac{b^2}{a^2}} \quad (2)$$

$$M = \frac{4\pi \, x \, A}{C} \quad (3)$$

The minor axis is indicated by the notation a and the major axis is indicated by the notation b. Symbol A indicates area and C indicates circumference [18].

2.4 Image Prediction

In this study, each image extracted using RGB, GLCM, and Shape features will be used as input for modeling using the BPNN method. So, the data is broken down into training data and testing data, each of which has 4 output targets, namely Itoh, Kristal, Ruby, and Pimpong.

BPNN is a supervised learning algorithm consisting of several parts, namely input layers, hidden layers, and output layers which then occur weight changes that connect each layer [21]. BPNN evaluates the error contribution approach of each neuron in a data series. It aims to modify the weights so that output mapping and neural network training can take place correctly [22]. Figure 9 shows an example of a BPNN architecture.

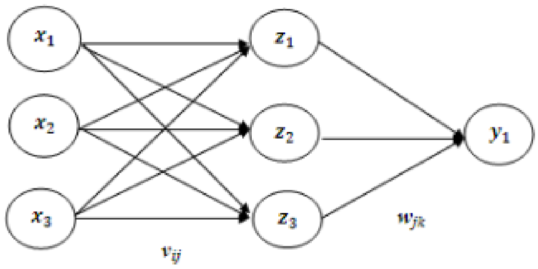


Figure 9 BPNN's architecture

Input layers are annotated using x_1, x_2, and x_3. While z_1, z_2, and z_3 are hidden layers, and y_1 is the output layer. The layers of the network are connected by the weight of each layer. The BPNN equation (4) can be described as follows:

$$y_k = f_k\left(\sum_{j=1}^{p} \quad wjkf_j\left(v_{0j} + \sum_{i=1}^{n} \quad x_i v_{ij}\right) + w_{0k}\right) \quad (4)$$

2.5 Evaluation

This step is carried out to find out the efficiency of the developed model. The classification results will be checked for accuracy to determine how close the test results are to the actual value [23]. Testing is carried out by equations (5).

$$Accuracy = \frac{CP}{TP} x \, 100\% \quad (5)$$

CP (Correct Prediction) is the sum of correct predictions, and TP (Total Prediction) is the sum of the overall predictions.

3. RESULT AND DISCUSSION

3.1 Data Collecting

Data in the form of longan leaf images were obtained independently by the author. The data was obtained from private gardens and gardens owned by private developers in the Semarang City area. The data comes from 4 different trees and fruit characteristics. The total data obtained from each tree amounts to 200 leaf blades, so the overall total of the 4 trees is 50 leaf blades. The leaves obtained from each tree are then sorted to obtain the leaves of the best color and shape. After the sorting process is carried out, the best 20 leaf blades are obtained from each tree which will then be documented. The leaf documentation process is carried out using a smartphone camera with a resolution of 12 megapixels. The image documentation technique is carried out by placing the object on a blank field, namely paper, then photographing it from a distance of 30 cm.

3.2 Pre-processing Data

After the longan leaf image is collected, the data is pre-processed. The goal is that the data to be processed has a good value so that the predicted results are close to real data.

Pre-processing the data performed is extracting the red component from the RGB image. The R (Red) component was chosen because between the object and the background is more contrast compared to the G (Green) and B (Blue) components. Furthermore, thresholding of RGB images is carried out to convert RGB images into binary images. The threshold value used is 0.6 to distinguish the object from the background. After successfully performing the threshold, a complement operation is performed so that the background is worth 0, and the object is worth 1, so that image processing is better. After performing the complement, morphological operations were then performed to perfect the segmentation results. The first morphological step performed is a closing operation, which is to combine the pixels around the object to reduce noise on the object. In this operation, the structuring element is added in a round shape with a radius of 5. Furthermore, the filling holes operation is carried out, which is to close the holes contained in the object so that there are no holes in the object that will affect the extraction results. Then, after combining pixels, to ensure that there is no noise left, an opening area operation is carried out to remove the noise. The limit of the value used is 5000, so if there is an object with an area below 5000, then the object will be eliminated or deleted.

3.3 Feature Extraction

After pre-processing the data, the next step is to perform feature extraction to distinguish one class from another to obtain the values to be used as modeling inputs. Before feature extraction is carried out, the data is broken into two parts, namely 60 training data images and 20 test data images (testing). The classes used are itoh class, kristal class, ruby class, and pimpong class.

The variables used are metric and eccentricity, where these variables are used to identify the shape of an object. To obtain metric variables, area and perimeter variables are used. Area variables are used to calculate the area of the object. Perimeter variables are used to calculate the circumference of the object. Next, the image is classified using the BPNN algorithm after the metric and eccentricity variables have been collected. The categorization stage is completed by combining input metrics and eccentricity factors. Target variables should then be compiled to distinguish one class from another. By offering a sequence based on the quantity of photos of each variety of longan, the targets are separated. The next step is to construct a BPNN architecture employing hidden layers as many as 10 and 5 and components in the form of inputs and targets. Following the construction of the network design, network training is performed to match the input value with the intended class, followed by output simulation. The network architecture training results were run using 2 inputs, 10 neurons on the first hidden layer, 5 neurons on the second hidden layer, and 1 neuron on the output layer, halting after the 19th iteration and 1000 epochs. The architecture view of the Learning Outcomes Network is shown in Figure 10. The accuracy rate of the network architecture training results is 70%. The results of network architecture training are then stored for use as image prediction testing.

3.4 Image Prediction and Evaluation

Five photos of each type were used in the image prediction stage, which involved testing the test data on as many as 20 photographs. Recalling the network architecture from the training results is used to administer the exam. Twenty photos of leaves serve as the test data input. The input test's accuracy as a result is 70% of the target. As

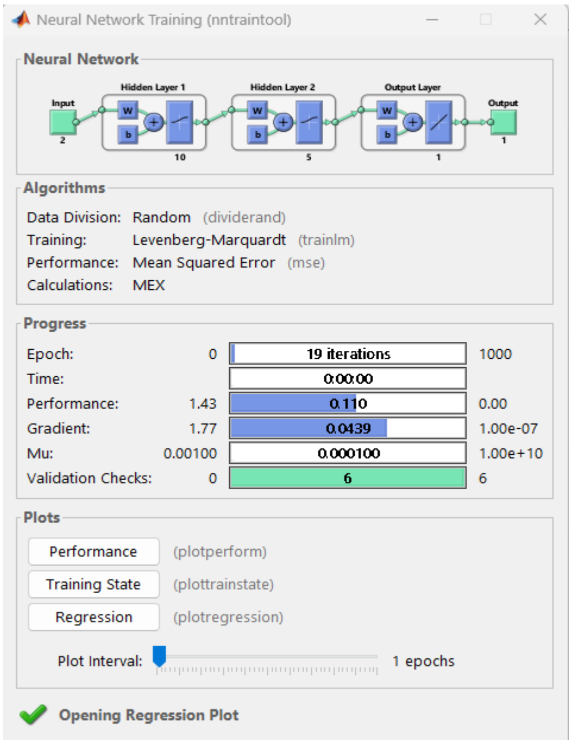


Figure 10 BPNN's training architecture

shown in Figure 11, the authors built a GUI-based interface using Matlab to make it simpler to test the model.

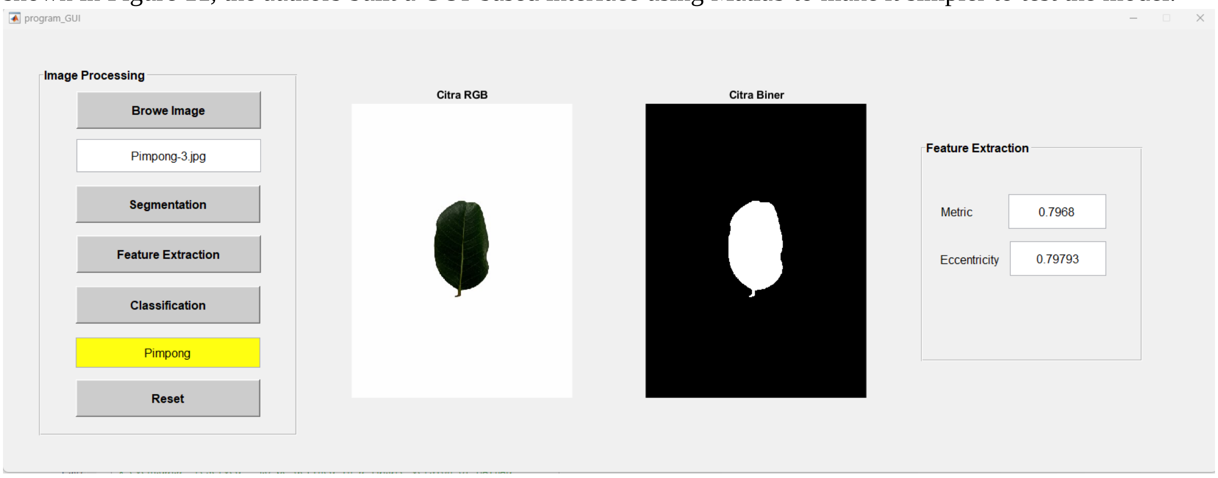


Figure 11 GUI Classification system for leaf types of longans fruit

4. CONCLUSION

The classification of Indonesia's various longan fruit varieties is the goal of this study. The Itoh longan, Crystal longan, Red / Ruby longan, and Pimpong longan are the four (four) different types of longans on which the classification is based. The pre-processing stage of the image-processing process involves matching the data obtained with the background and size. In order to determine the value of each feature extraction on each variety of longan leaf, the data is also analyzed using the Matlab application. This study employed the Back-propagation Neural Network (BPNN) algorithm's shape extraction feature to categorize various kinds of longan fruit based on the morphology of their leaves. The BPNN approach can be used to detect differences in leaf morphology. To boost performance, longan fruit leaves are identified using BPNN with eccentricity and metric parameters. As a result of training and testing, the model's accuracy was 70%. This low degree of accuracy is owing to the poor image quality obtained. It is envisaged that future investigations would use higher-quality imaging to achieve a higher level of accuracy. With the aforementioned accuracy results, more research with higher data quality is required to acquire better outcomes.

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