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MORPHOLOGICAL AND TEXTURAL FEATURE EXTRACTIONS FROM FUNGI IMAGES FOR DEVELOPMENT OF AUTOMATED MORPHOLOGY-BASED FUNGI IDENTIFICATION SYSTEM

Ekstraksi Fitur Morfologi dan Tekstur Citra Jamur untuk Pengembangan Sistem Identifikasi Jamur Otomatis Berbasis Morfologi

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ABSTRACT

Due to widely varied microscopic shapes, fungal classification can be performed based on their morphological features. In morphology-based identification process, feature extraction takes an important role to characterize each fungal type. Previous studies used feature extraction of fungal images to detect the presence of fungal. In this study, morphological and textural features were extracted to classify three types of fungi: Aspergillus, Cladosporium *and* Trichoderma*. Geometry and moment were used as morphological features. To perform textural feature extraction, the local binary pattern (LBP) and gray level co-occurrence matrix (GLCM) feature extraction method were used. We compared the implemented feature extraction methods in order to get the best classification result. The result showed that geometrical features has the accuracy of 65%, higher than that of LBP (60%), GLCM (45%), and moment accuracy (55%). This suggested that geometric features is important for fungal classification based on their morphology.*

Keywords*: Fungal, fungal classification, Feature extraction, Geometry, Moment, Local binary pattern, Gray level co-occurrence matrix.*

ABSTRAK

Karena bentuk mikroskopisnya yang sangat bervariasi, klasifikasi jamur dapat dilakukan berdasarkan ciri morfologisnya. Dalam proses identifikasi berbasis morfologi, ekstraksi ciri berperan penting untuk mengkarakterisasi setiap jenis jamur. Penelitian-penelitian yang dilakukan sebelumnya melakukan ekstraksi ciri citra jamur untuk mendeteksi keberadaan jamur. Dalam penelitian ini, fitur morfologi dan tekstur diekstraksi untuk mengklasifikasikan tiga jenis jamur: *Aspergillus*, *Cladosporium* dan *Trichoderma*. Geometri dan momen digunakan sebagai ciri morfologi. Untuk melakukan ekstraksi ciri tekstur, digunakan metode ekstraksi ciri local binary pattern (LBP) dan gray level co-occurrence matrix (GLCM). Kami membandingkan metode ekstraksi fitur yang diterapkan untuk mendapatkan hasil klasifikasi terbaik. Hasil penelitian menunjukkan bahwa fitur geometri memiliki akurasi 65%, lebih tinggi dari LBP (60%), GLCM (45%), dan akurasi momen (55%). Ini menunjukkan bahwa fitur geometris penting untuk klasifikasi jamur berdasarkan morfologinya.

Kata Kunci: Jamur, klasifikasi jamur, ekstraksi ciri, Geometri, Moment, Local binary pattern, Gray level co-occurrence matrix.

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INTRODUCTION

Microorganisms play an indispensable role in human life. They are widely used for many purposes, such as fermented food production (Asmoro 2021), traditional medicine (Rahmawati 2015), and agricultural products (Sari et al. 2015). In addition, various microorganisms can be studied for drug discovery (Waluyo et al. 2021). As of 2017, around 2.273 species of fungi in Indonesia have been listed in the biodiversity status (Darajati et al. 2016).

Identification of microbes is generally conducted based on a molecular approach. Specific target sequence in their genetic materials is used to classify microbes. However, microscopic methods or morphological observation are considered proper methods to help in the drug discovery process because they can describe how disease processes unfold and potential therapies might intervene (Bullen 2008).

About 148,000 species of fungi have been identified so far (Zhou and May 2022), which is part of an estimated 2.2 to 3.8 million species currently present in this world (Hawksworth and Lücking 2017). Those fungi have many different morphological features used by fungal taxonomists for fungal classification. Thus, a trained and experienced person performs such an identification approach.

Fungi are a type of microbes that mostly live in colonies. An appropriate feature extraction method is needed to get the features that adequately represent fungi's morphological and special characteristics. Image-based identification has been utilized widely to recognize an object based on its features. Morphological and textural features are the most common features used in identification based on a microbial image. In earlier research, features extracted from microscopic images are geometry, texture, and shape.

Geometric features are features that represent the shape of an object. Some geometric features often used include area, metric, eccentricity, and perimeter, while textural features describe light intensity changes on the surface of an object. Two widely used methods for textural feature extractions are local binary pattern (LBP) and gray level co-occurrence matrix (GLCM).

Previous research (Chayadevi and Raju 2012) used geometric features to classify and cluster microbes. The geometric features that were used in this study include area, perimeter, circularity, and compactness. Another study (Xiaojuan et al. 2008) used moment feature extraction for microbe image recognition. Moment feature was chosen because this feature will not be affected either by scale or direction. Besides geometry and moments, textural features are also often used for image recognition. Local binary pattern (LBP) and gray level co-occurrence matrix (GLCM) are commonly used methods for extracting texture features. LBP is a representation of changes in light intensity on the surface of the object. Textural features are represented by 256 numbers of values which are the frequency of occurrence of the LBP value. LBP method has been widely used in the field of image recognition, such as facial recognition (Nhat and Hoang 2019), plant classification (Ibrahim et al. 2018), and vegetable diseases (Pujari et al. 2014). Although has a relatively low computational complexity, LBP is considered quite powerful since it has a robustness under grayscale invariance, illuminative variation, and discriminative power (Ibrahim et al. 2018). Unlike LBP, GLCM represents textural features with four numbers of values, which are contrast, correlation, energy, and homogeneity. Satoto et al. (2020) used GLCM feature extraction method to identify bacteria on microscopic images, while Rawat et al. (2015) detects leukemia on microscopic images using GLCM feature extraction method.

In previous studies, feature extraction of fungus based on images has been carried out both through classical machine learning method (Hardy et al. 2017, Wu et al. 2018) and deep learning methods (Liu et al. 2020, Lv et al. 2020, Koo et al. 2021). Previous studies only focused on detecting fungi in an image. In this study, we extracted fungal morphological and textural features, which will be largely beneficial for development of automated fungal morphology-based identification system. There have not been many studies on the classification of the genus of fungi using microscopic image datasets, so this study was started by using the three genera that are considered the easiest to distinguish

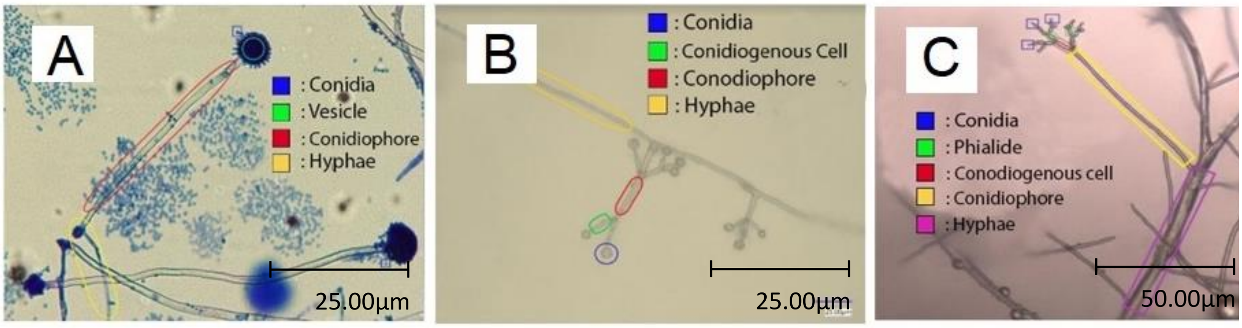

Figure 1. Structures of *Aspergillus*(A), *Trichoderma* (B), and *Cladosporium* (C)

from a microbiological point of view. The three genera namely: Aspergillus, Cladosporium, and Trichoderma. The dataset was deposited in Biotech Center-BPPT Microbial Collection Center (BioMCC) (currently became part of a collection in Indonesia Culture Collection (InaCC) of the National Agency for Research and Innovation (BRIN)). Local binary pattern (LBP) and gray level co-occurrence matrix (GLCM) were used for feature extraction. Geometry features consist of values of circularity, area, eccentricity, and metric. On the other hand, the shape feature is based on the moment value. These values are then used to classify the sample using k-nearest neighbor (KNN) method. This research aims to perform feature extraction of fungal images with the methods mentioned above, use them to classify fungal genera, and compare the performance of each feature extraction method used. Applying feature extraction methods based on morphology and texture from images is expected to assist the identification process, which can accelerate exploration for drug discovery.

MATERIALS AND METHODS

Location and time

This research was conducted from May to October 2022. The study was performed at Artificial Intelligence and Cyber Security Research Center, Research Center for Vaccine and Drug, and Research Center for Applied Microbiology, National Research and Innovation Agency.

Materials

To determine the features that need to be assessed, an understanding of the morphology of fungi is essential. The dataset used for this study is a ground truth image dataset of fungi. As mentioned earlier, this research will use 3 genera of fungi (*Aspergillus*, *Cladosporium*, and *Trichoderma*) as the object material. These fungi share several common features. They also have several features that differentiate one from another. Parts of fungal structure to be observed were conidia, vesicle, conidiophore, hyphae, conidiogenous cell, and phialide. Parts for each fungal genus are shown in Figure 1(A) *Aspergillus*, Figure 1(B) *Trichoderma*, and Figure 1(C) *Cladosporium*.

Method

The features extracted from the images are texture, geometry and moment. In order to extract textural features, LBP and GLCM method are applied to the grayscale images. Geometry and moment features, on the other hand, are extracted from the binary images. The dataset contains of 60 fungus images, 20 images for each genus. The flowchart methodology

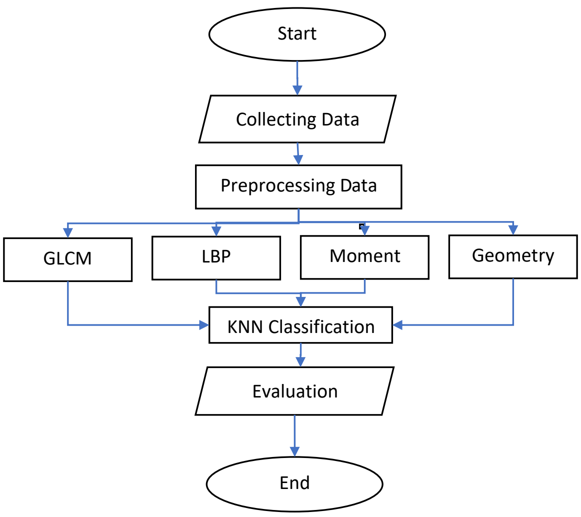

Figure 2. Flow Chart of Methodology Research

of this research can be seen in the Figure 2.

Local Binary Pattern

The ground truth grayscale dataset obtained texture features with the Local Binary Pattern (LBP) method. Each pixel in the image dataset was compared with the pixels around it (neighbor) to get the LBP code. The result of this process is a histogram of the appearance of pixels that contain vectors with 256 elements. Examples of LBP feature extracted images can be seen in Figure 3.

Gray Level Co-occurrence Matrix

Gray level co-occurrence matrix (GLCM) is the other feature extraction method that extracts textural features. Texture features with the GLCM method were obtained using the ground truth grayscale dataset. One pixel is compared to other pixels in the fixed distance(d) and angle(ɵ). The angle orientations are set in 4 directions, which are 0º, 45º, 90º, and 135º with a distance of 1 pixel.

Four features were generated for each image. Those features are contrast, entropy, energy, and homogeneity. Contrast is the number of local variations for an image's grey level. In contrast, entropy is the value of irregularity in an image. If the overall value of the entropy of an image is the same, then its entropy value is considered high. Energy is a distribution of the pixel intensity of an image. The last feature is homogeneity which describes the similarity of pixel distribution in an image.

Geometrical Features

To obtain the geometrical features of an object, first, the image has to be segmented, so it appears as one single object, separated from the background of the image. The features are then extracted from the binary image. These features are area, metric, eccentricity, and perimeter. The value of the area is the number of pixels whose value is one. Metric or circularity is the ratio between the surface area and an object's circumference, representing the amount of roundness. Eccentricity is the ratio of the distance between the ellipse's foci and its major axis length. Perimeter is the circumference of an object, calculated from the number of pixels connected in the object (Arora and Dhir 2020).

Besides those features, many other geometrical features can be extracted as in previous research (Lin et al. 2020), such as convex area, bbox area, major axis length, minor axis length, equivalent diameter, mean intensity, solidity, and orientation. This study conducted an experiment with 4 number of geometrical features (area, metric, eccentricity, perimeter) and 11 numbers of geometrical features (area, convex area, bbox area, major axis length, minor axis length, perimeter, equivalent_diameter, mean intensity, solidity, eccentricity, and orientation) for fungal image classification.

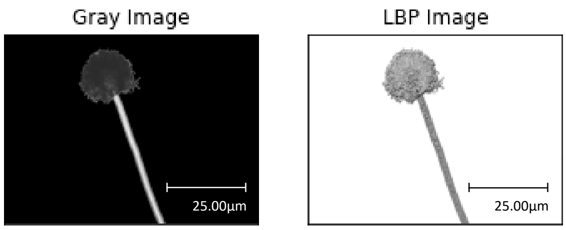

Figure 3. The example of local binary pattern image result

Moment Features

A moment is used to describe image's shape, there are many different varieties of moments such as invariant moments (Hu moments), Zernike moments (Celebi and Aslandogan 2005), also central moments (Demi et al. 2000). A moment as shape based descriptor can indicate image's characteristics such as holed objects, partially occluded objects, and complex objects with multiple disconnected regions, employing boundary and interior pixels to get the properties. Because of this reason, moments can be applied to common shapes and are less susceptible to distortions.

Invariant moments (Hu moments) can be used to extract properties of an object in the image in form of position, area, orientation and many others (invariant to translation, rotation, and scaling). Zernike moment is used to describe objects in an image by allowing independent moment invariant to be constructed to an arbitrarily higher order (D'Silva and Bhuvaneswari 2015).

The central moment is used to raise the class of nonlinear filters and enhance lines, edges, corners, and intersections between discontinuities. The Center of the central moment can be defined and employed to evolve a new contour tracking procedure (Demi et al. 2000). The experiment in this paper focused on Hu moments and central moments to get the shape of the fungus' image. The number of central moment features was 16 while the hu moment was 7, so the total number of feature moment used was 23.

Validation

K-Nearest Neighbor (K-NN) is a simple classification method. K-NN only has two parameters: distance and number of neighbors (Zhang et al. 2019). K-NN classifies an entity based on the distance of the entity to its neighbors. K in K-NN represents the number of nearest neighbors of the entity whose majority class is the class of the newly identified entity. After each image's features are obtained, the classification is carried out using the K-NN classification method to see the performance of each feature in determining the genus. The dataset was divided into training and testing data, with a ratio of 80% for training data and 20% for testing data.

Recall and precision calculations are performed to see each method's performance. Recall and precision are the most common evaluation methods for identification tasks (Parvin and Mehedi Hasan 2020). Precision indicates the ratio of correctly classified positive items to the total of positive classified items. Meanwhile, recall explains the ratio of correctly classified positive items to a total of correctly classified positive items and wrongly classified negative items. In short, precision can be seen as a quality measurement technique and recall as a quantity measurement.

RESULTS AND DISCUSSION

Each feature that was generated by each method was used for classification process. The classification process used a K-NN classifier with K=1 to K=5. the first experiment was to see the accuracy of each feature in classifying images. The result can be seen in Figure 4.

Geometry 1 is the result of geometric feature extraction with 4 features, while geometry 2 is the result of geometric feature extraction with 11 features. From the single feature classification results, as seen in Figure 4, the best average accuracy features were geometry 1's features and LBP. Geometry 1's features obtain the highest accuracy with a value of K=1. The results showed that the best accuracy average obtained by the geometric feature extraction method was 65%, while the LBP method was 60%, GLCM was 45%, and the moment was 55%. This moderate accuracy is most likely the result of a lack of data. The limited dataset is known to cause overfitting model (Ying 2019). In addition, the range of accuracy in this study is also not much different from the accuracy obtained by Li et al. (2021) using microscopic image objects and the same feature extraction method as well. Recall and precision calculations were carried out by performing a separate classification for each feature with the KNN classification (K=1). Table 1 shows that the performance of geometry 1's features in recognizing the three classes of fungus was the best compared to other features'. The accuracy of features in recognizing objects is already high, especially for the *Aspergillus* and *Trichoderma* classes. The highest F1-score was obtained by the *Aspergillus* class, meaning that geometric 1's feature can identify the fungus with high accuracy and has good information retrieval ability.

Geometry 2's feature performance can be seen in Table 2. Geometry 2's features used more features but got a relatively lower F1-score. That result proves that geometric 2's features, such as convex area, bbox area, major axis length, minor axis length, equivalent_diameter, mean intensity, solidity, and orientation are uncorrelated for identifying the fungi.

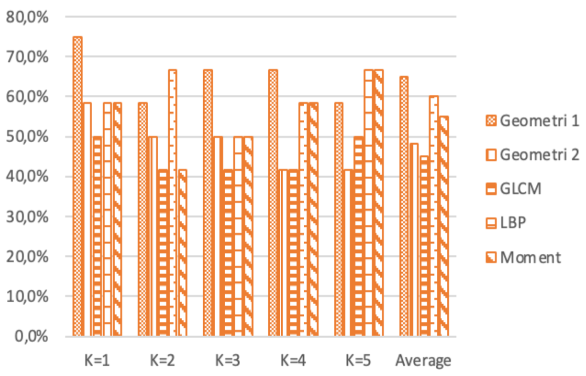

Figure 4. Accuracy of fungus classification using morphological and textural features with KNN classifier

Table 1. Class recall and precision of extraction classification of Geometry 1's features

Class	*Precision*	*Recall*	*F1-score*	*Support*
Aspergillus	1.00	0.75	0.86	4
Cladosporium	0.57	1.00	0.73	4
Trichoderma	1.00	0.50	0.67	4
Accuracy			0.75	

Table 2. Class recall and precision of classification of Geometry 2's feature extractions

Class	*Precision*	*Recall*	*F1-score*	*Support*
Aspergillus	0.33	0.25	0.29	4
Cladosporium	0.43	0.75	0.55	4
Trichoderma	0.50	0.25	0.33	4
Accuracy			0.42	

Table 3. Class recall and precision of LBP features extraction classification

Class	*Precision*	*Recall*	*F1-score*	*Support*
Aspergillus	1.00	0.50	0.67	4
Cladosporium	0.43	0.75	0.55	4
Trichoderma	0.67	0.50	0.57	4
Accuracy			0.58	

Table 4. Class recall and precision of GLCM features extraction classification

Class	*Precision*	*Recall*	*F1-score*	*Support*
Aspergillus	0.60	0.75	0.67	4
Cladosporium	0.50	0.50	0.50	4
Trichoderma	0.30	0.25	0.29	4
Accuracy			0.50	

Table 5. Class recall and precision of classification of moment feature extraction

Class	*Precision*	*Recall*	*F1-score*	*Support*
Aspergillus	0.67	0.50	0.57	4
Cladosporium	0.50	1.00	0.67	4
Trichoderma	1.00	0.25	0.40	4
Accuracy			0.58	

The F1-score value, which is not much different from each class, was generated by the textural features using the LBP method with a range of 0.55-0.67, as shown in Table 3. The highest precision value was obtained by the *Aspergillus* class, while the *Cladosporium* class obtained the lowest precision value. While the *Cladosporium* class obtained the highest recall value. Although the accuracy value of the *Aspergillus* class was high, the information retrieval ability was low, which is only 0.5.

Table 4 shows the textural features produced by the GLCM method obtained f1-score values that are almost the same as LBP for the *Aspergillus* and *Cladosporium* classes. However, the *Trichoderma* class got the lowest score for both the recall and precision values. This means that the textural features using the GLCM method are not good enough to identify the *Trichoderma* class.

Table 5 shows that the moment feature generated almost the same performance as the LBP in the *Trichoderma* class. Although the classification results show perfect accuracy, the ability to retrieve information is still very low, namely 0.25. Like other classes, there is no significant increase in performance.

According to this experiment, the classification using geometry 1's features gives the best result because they give higher recall, precision, and f1-score for

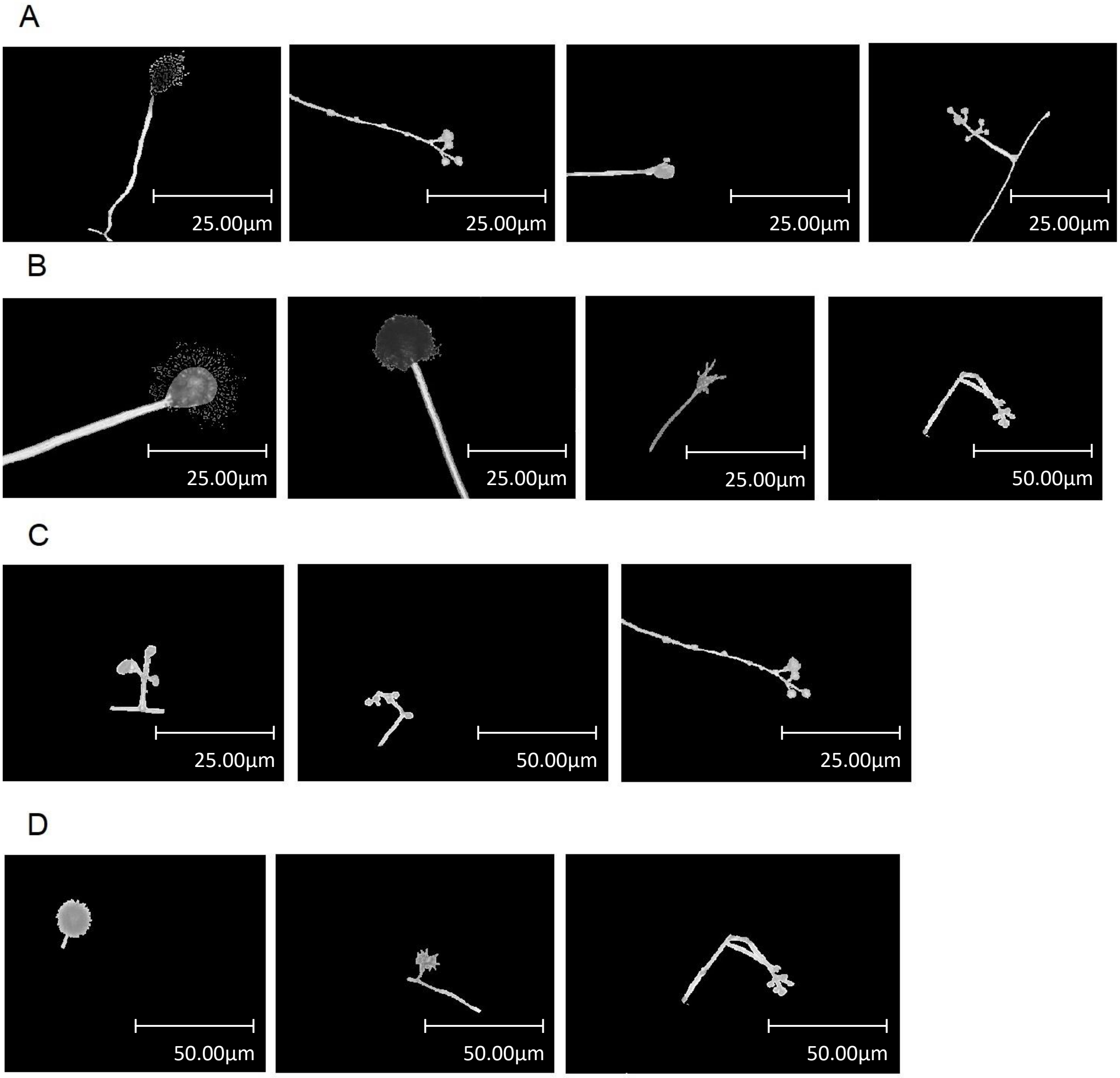

Figure 5. Sample of images that failed to correctly classify using geometry 1 features (A), Sample of images that correctly classify by geometry 1 features (B), Sample of images that failed to be correctly classified by LBP features(C), Sample of images that images correctly classify by LBP features (D)

each fungus' genus than the others features.

Furthermore, the classification results were analyzed by looking at the images that succeeded and failed to be correctly classified by each feature extraction method. Examples of failed classified images can be seen in Figure 5.

Figure 5 shows the images that failed to be correctly classified by Geometry 1's features. Incorrect classification is led by a lack of data, which cannot provide enough features fed to the classification model to improve its learning. Few data give a shallow understanding of the model in segregating each genus' characteristics. In addition, for some images, the geometric features were not extracted perfectly because the conidia were separated from the object. As a result, the process of calculating geometric features became inaccurate.

The images with small object proportions failed to be extracted well using the LBP feature. Not many features can be generated to describe the texture of the image itself, as well as in the GLCM feature extraction case. Small objects lack the information needed to differentiate them from the background (Bai et al. 2018).

For moment feature extraction, the accuracy results obtained were relatively low. As with other features, data shortage constraints are a problem. Moment feature extraction cannot be expected to extract high-level features; thus, a large training data set is needed (Kumar and Bhatia 2014). Furthermore, the effective application of deep learning to the processing of biological and medical images supports the development of deep learning for the processing of microscopic imaging, which might significantly advance the study of materials (Ge et al. 2020).

CONCLUSION

In this study, we used the proposed methods, namely geometry, LBP, GLCM, and moment feature extraction, to identify and classify microscopic images of fungi. Based on the results, the highest accuracy of fungus classification was obtained using geometric feature extractions, while the moment features extraction obtained the lowest accuracy. The difficulty faced had to do was a limited number of datasets. The conclusion that can be drawn from this research is although the geometric features get the best accuracy, the accuracy obtained by the geometric features themselves is not high enough. It can be the basis that the classical feature extraction method is not sufficient to produce a fungal identification model. Therefore, a deep learning approach for feature extraction of fungi is recommended for further research. Multiple classifier methods can also be used to improve accuracy by using a combination of several features.

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