REKAYASA
Journal of Science and Technology
https://journal.trunojoyo.ac.id/rekayasa

Rekayasa, 2021; 14(3): 407-415
ISSN: 0216-9495 (Print)
ISSN: 2502-5325 (Online)

Classification of Dermoscopic Image of Skin Cancer Using the GLCM Method and Multi-SVM Algorithm

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DOI: https://doi.org/10.21107/rekayasa.v14i3.12213

ABSTRACT

The development of abnormal skin pigment cells can cause a skin cancer called melanoma. Melanoma can be cured if diagnosed and treated in its early stages. Various studies using various technologies have been developed to conduct early detection of melanoma. This research was conducted to diagnose melanoma skin cancer with digital image processing techniques on the dermoscopic image of skin cancer. The diagnosis is made by classifying dermoscopic images based on the types of Common Nevus, Atypical Nevus or Melanoma. Pre-processing is done by changing the RGB image to grayscale (grayscaling), smoothing image using median filtering, and image segmentation based on binary images of skin lesions. The value of Contrast, Correlation, Energy and Homogeneity obtained from the texture feature extraction of the GLCM method is used in the next step, which is the classification process with the Multi-SVM algorithm. The proposed research method shows high accuracy results in diagnosing skin cancer.

Key words *: skin pigment, cancer, image analysis, Mult-SVM algorithm*

INTRODUCTION

Organs that require special attention are the skin that forms the largest part of the human body that is most visible. Healthy skin shows a person's level of health. Manicured body skin will become the owner's pride. Skin that is maintained does not only add to its owner's aesthetics but also has the main functions as body protection, temperature regulation, vitamin production and water storage (Rogers & Balooch, 2016). According to Rogers (Rogers & Balooch, 2016) skin condition can be affected by his health such as the presence of certain diseases. Other influences are skin exposed to harmful environmental factors and other conditions that occur due to aging. The skin is very important for one's health and well-being.

One type of cancer in humans that is commonly found is skin cancer. In some countries, the disease is experiencing alarming growth rates, such as cases in the United States, New Zealand and Australia. Some of the main causes of melanoma and non-melanoma skin cancer are exposure to ultra-violet (UV) radiation (Bharadwaj et al., 2019).

Based on data collected since 1975, melanoma cases that occurred in the United States grew to tripled in 2012, reaching 22.9 people per 100,000 people. Of these, the death rate is 2.7 per 100,000 and in the last 2 decades it has been relatively stable (Brunssen et al., 2016).

Abnormal multiplication of pigment-producing cells in skin color causes a skin cancer called melanoma, or malignant melanoma (Esfahani et al., 2016). Melanoma can be cured if diagnosed and treated in its early stages. But this type of skin cancer can also grow deeper into the skin and even spread to other parts of the body if diagnosed too late (Jain et al., 2015). Meanwhile, the differentiation carried out in the early growth stages to distinguish melanoma and other benign moles is a challenging task, even for experienced dermatologists (Esfahani et al., 2016).

Various studies using various technologies have been developed to conduct early detection of

Article History:
Received: June, 30th 2021; **Accepted**: November, 17th 2021
Rekayasa ISSN: 2502-5325 has been Accredited by Ristekdikti (Arjuna) Decree: No. 23/E/KPT/2019 August 8th, 2019 effective until 2023

Cite this as:
Hasanah, R.L & Riana, D. (2021*). Classification of Dermoscopic Image of Skin Cancer Using the GLCM Method and Multi SVM Algorithm*. Rekayasa 14 (3). 407-415.
doi: https://doi.org/10.21107/rekayasa.v14i3.12213.

melanoma, one of which is the dermoscopy method. Dermoscopy microscopy, also called *epiluminescence*, is a method used to obtain an image of an enlarged and illuminated area of the skin with the aim of increasing the detail of spots on the skin (Mishra & Celebi, 2016). Melanoma detection can be done using digital image processing techniques on dermoscopic images of skin cancer. This technique can help and improve the accuracy of a dermatologist in diagnosing melanoma.

Research conducted by (Hadi et al., 2015) diagnoses skin cancer using ABCD characteristics, K-Means and CCL algorithms that are integrated into the DEWA Framework. Based on 29 images tested, 24 images were detected correctly based on ground truth data, so that the resulting accuracy was 83%. Other studies by (Jain et al., 2015) diagnose melanoma skin cancer using image processing tools. Texture, size and shape analysis for image segmentation and feature extraction stages were carried out to check various Melanoma parameters such as Asymmetry, Border, Color, Diameter (ABCD), etc. The results obtained from the study are that the proposed system can be used effectively by patients and doctors to diagnose skin cancer more accurately.

While research by (Esfahani et al., 2016) compares the Convolutional Neural Network (CNN) method with other methods used in previous studies, to detect melanoma skin cancer. The result is the proposed method that CNN produces the highest accuracy of up to 81%. Other studies on the classification of skin diseases using CNN and the combination of CNN (Polat & Koc, 2020) in seven classes showed very good results, but the dataset used was different from this study. Although different dataset, but still discuss about malignant melanoma in skin tissue that can lead to death (*Halk Sağlığı Genel Müdürlüğü*, n.d.). Computers can be alternatives such as Computer Aided Diagnosis (CAD) for early detection (Oktay Yıldız, 2019). Non-invasive skin imaging technique technology or dermoscopy can prevent melanoma because it can be treated simply and on target (Celebi et al., 2007). Some studies use CNN as a classification algorithm. CNN accuracy is greatly influenced by the number of input convolution images use (*Dermnetnz*, n.d.).

Until now, machine learning techniques were commonly used in early detection of dermoscopy. There are researchers who use four different models, namely variations in k-NN (k-Nearest Neighbor) (Odeh & Baareh, 2016). Even a hybrid approach (Dalila et al., 2017) for the detection of melanoma and benign skin lesions. Image segmentation techniques are applied to obtain features using the K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) classification algorithm (Abbes & Sellami, 2017). Then, skin lesions classified using SVM have been proposed (Abbes & Sellami, 2017).

Furthermore, there are researchers who use different models for demoscropy imagery, namely SCM for the same PH2 dataset as this study and obtain excellent results but for the classification of two classes (Filho et al., 2018). While this study uses classifications for three classes, different from (Filho et al., 2018). Another approach is the pixel classification and fuzzy histogram threshold in melanoma from dermoscopy images (Garcia-arroyo & Garcia-zapirain, 2019), while (Serte & Demirel, 2019) proposes a wavelet-based convolutional neural network based on wavelet for two classifications of malignant melanoma and seborrheic keratosis.

Use of GLCM feature extraction from fractal and regional based texture analysis algorithm (FRTA) (Chatterjee et al., 2019), the GLCM feature was also used in this study. Multi-Class Multi-Level (MCML) classification for multi-skin lesions is proposed (Hameed et al., 2020). Other researchers segmented dermoscopy images by using Local Binary Pattern Clustering (LBPC) and extracting them into a feature form from and classified with Feed Forward Network (Pereira et al., 2020). Another approach in the classification of skin cancer uses PCA (Amin et al., 2020). The use of classifications in three classes has been carried out in different datasets from this study namely classes including benign, dysplastic, and melanoma (Khan et al., 2019).

This type of feature with the IcNR approach to the classification of skin lesions has been done by proposing a new segmentation of convolutional neural networks (Xie et al., 2019). Another segmentation is proposed with a Histogram Based Estimation algorithm grouping for skin lesion segmentation (Hawas et al., 2019). The researchers (Tan et al., 2020) proposed a hybrid method of Particle Swarm Optimization (HPSO) combined with CNN to detect skin lesions. This research was conducted for the classification of dermoscopic images of skin cancer using the GLCM method and

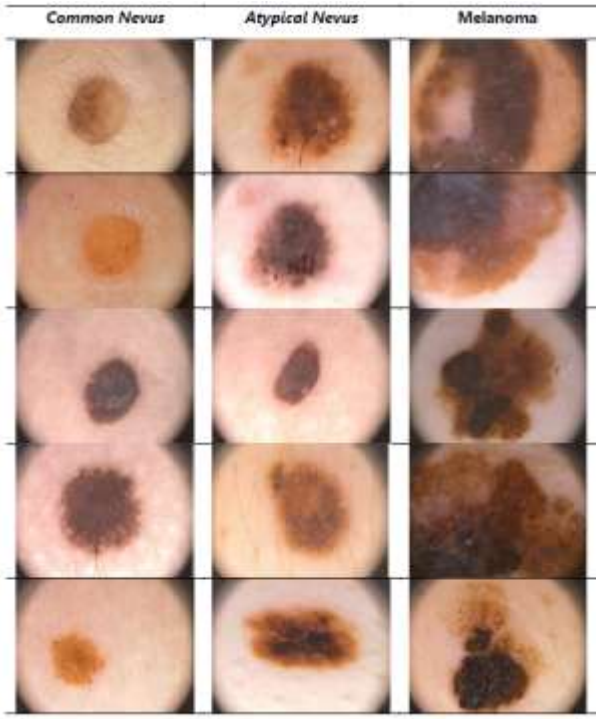
the Multi-SVM algorithm for the detection of melanoma skin cancer.

METHODS

Dataset

The image used in this study is a dermoscopic image from the Dermatology Service of Pedro Hispano Hospital, Matosinhos, Portugal and accessed online (Mendonca et al., 2013). The dataset consists of 200 8-bit RGB dermoscopic images, consisting of 80 *Common Nevus* images, 80 *Atypical Nevus* images, and 40 Melanoma images in BMP format. Besides, there are also lesion images from each dermoscopic image in the form of binary images with BMP format. The training was carried out by taking 45 dermoscopic images along with images of their skin lesions, each type of skin cancer using 15 training images. While testing is done by taking 15 dermoscopic images along with the image of skin lesions, each type of skin cancer using 5 testing images. Table 1 shown some dermoscopic images used in this study.

Table 1. Examples of Dermoscopic Images of Skin Cancer



Source: (Mendonca et al., 2013)

Proposed Method

The image processing is done by several processes such as grayscaling, median filtering, segmentation of skin lesions, feature extraction of the GLCM method, then classified with the Multi SVM. The dermoscopic image processing of skin cancer can be illustrated in Figure 1.

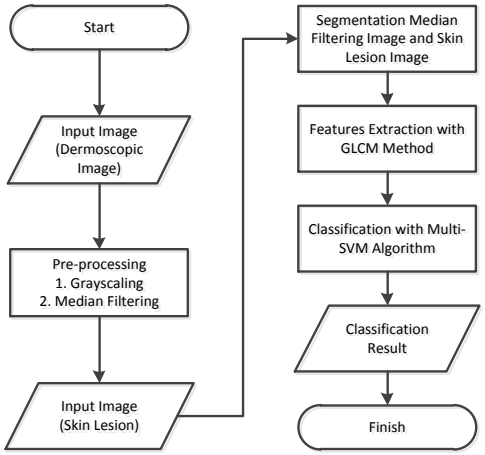


Figure 1. Dermoscopic Image Classification of Skin Cancer Flowcharts

GLCM (Gray Level Co-Occurrence Matrix)

To retrieve image information, feature extraction is performed on texture features that are calculated based on the Gray Level Co-Occurrence Matrix (GLCM). GLCM textures as originally described in 1973 by Haralick and others. The GLCM functions characterize the textures of an image by calculating how often a pair of the pixel with gray-level or value i occur either horizontally, vertically, or diagonally to adjacent pixels with the value j, where i values and j values represent gray level values in the image (Preetha & Jayanthi, 2018). The texture features used are Contrast, Correlation, Energy and Homogeneity with the following feature equations:

- Contrast returns a measure of the intensity contrast between a pixel and its neighbor over an image (Preetha & Jayanthi, 2018). The following if contrast formula:

$$\text{Contrast} = \sum_{\text{i,j=0}}^{N-1} P_{ij}(i-j)^2$$

- Correlation is the measure of how correlated a pixel is to its neighbor in an image (Preetha & Jayanthi, 2018). The following if correlation formula:

$$\text{Correlation} = \sum_{\text{i,j=0}}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2}$$

- Energy also known as uniformity or Angular Second Moment (ASM) is the sum of squared elements in the GLCM (Preetha & Jayanthi, 2018). The following if energy formula:

$$\text{Energy} = \sum_{i,j=0}^{N-1} (P_{ij})_2$$

- Homogeneity is the measure of closeness of the distribution of elements in the GLCM (Preetha & Jayanthi, 2018). The following if homogeneity formula:

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i-j)^2}$$

Multi-SVM (Multi Support Vector Machine)

Initially it was proposed, Support Vector Machine (SVM) is one of the binary classifier models. Many researchers tend to expand SVM into a multi-classification classifier to apply this model to the problem of multi-class classification (Xu et al., 2017). Two of the most widely used approaches for multi-class SVM classification are the One-Against-All (OAA) and the One-Against-One (OAO) approaches. The winner-takes-all strategy applies to the OAA framework to differentiate each class from all other classes. In the OAO approach, a dedicated classifier is trained for each of all possible pairs of classes (Lajnef et al., 2015).

RESULTS AND DISCUSSION

Grayscaling

In the process of image processing, the stages of pre-processing need to be done to prepare the image before it is processed. In the case of skin cancer dermoscopic image processing, the original image that has the RGB format is converted to a Grayscale format image. This is done because the texture feature of the GLCM that will be extracted at a later stage is the gray matrix value of an image. In addition the grayscaling process is carried out to simplify the image so that it is easier when processed. Figure 2 (a), (d), (g), (j), (m) and (p) shows an example of the original image of each type of skin cancer. Figure 2 (b), (e), (h), (k), (n) and (q) is an example of the image of the grayscaling process.

Median Filtering

After changing into a grayscale format image, the second pre-processing is carried out by applying the Median Filtering method to the grayscaling image. This method is used to reduce existing noise in the image, so that the image quality becomes better. Figure 2 (c), (f), (i), (l), (o) and (r) is an example of the image of the median filtering process.

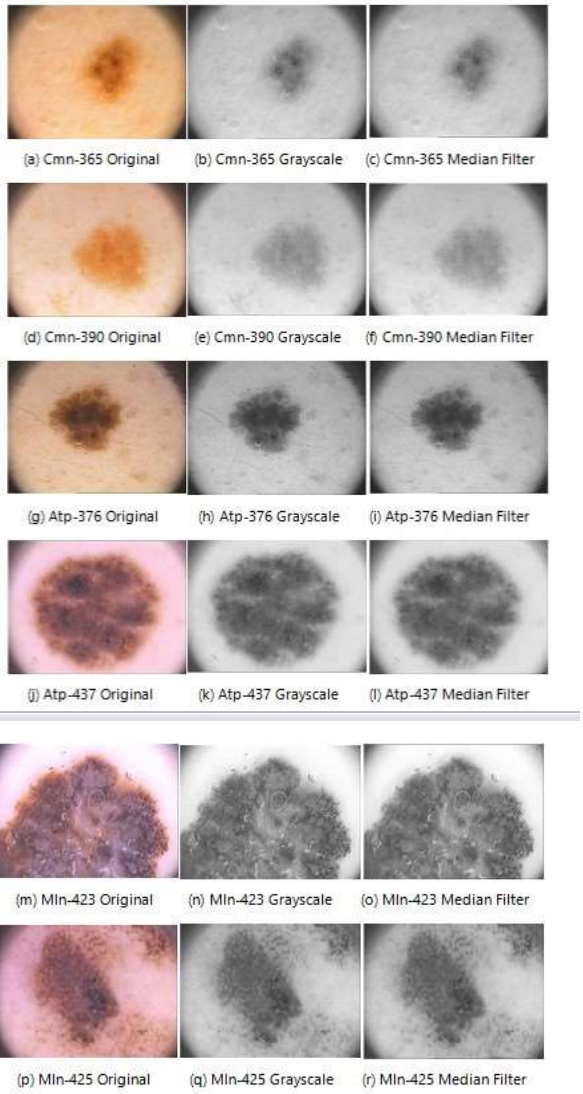


Figure 2. Original Image, Grayscale Image and Median Filter Image

Segmentation

An important part of the skin cancer detection process is to segment the correct area of the location of skin lesions because this stage is the stage where the targeted area must be as close as possible to the actual skin lesion (Aljanabi et al., 2018). Skin lesion images are available in the dataset used and are in the form of a binary black and white images. White indicates diseased skin, while black is considered background. Figure 3 (a), (c), (e), (g), (i) and (k) is an example of the image input of the skin lesion.

The image of the skin lesion is then used for the segmentation process. This segmentation process needs to be done to remove the background in the dermoscopic image of skin

cancer as a result of the Median Filter process based on the image of the skin lesion, so that the image processed at a later stage no longer has an unnecessary background. Figure 3 (b), (d), (f), (h), (j) and (l) is an example of a dermoscopic image of segmented skin cancer.

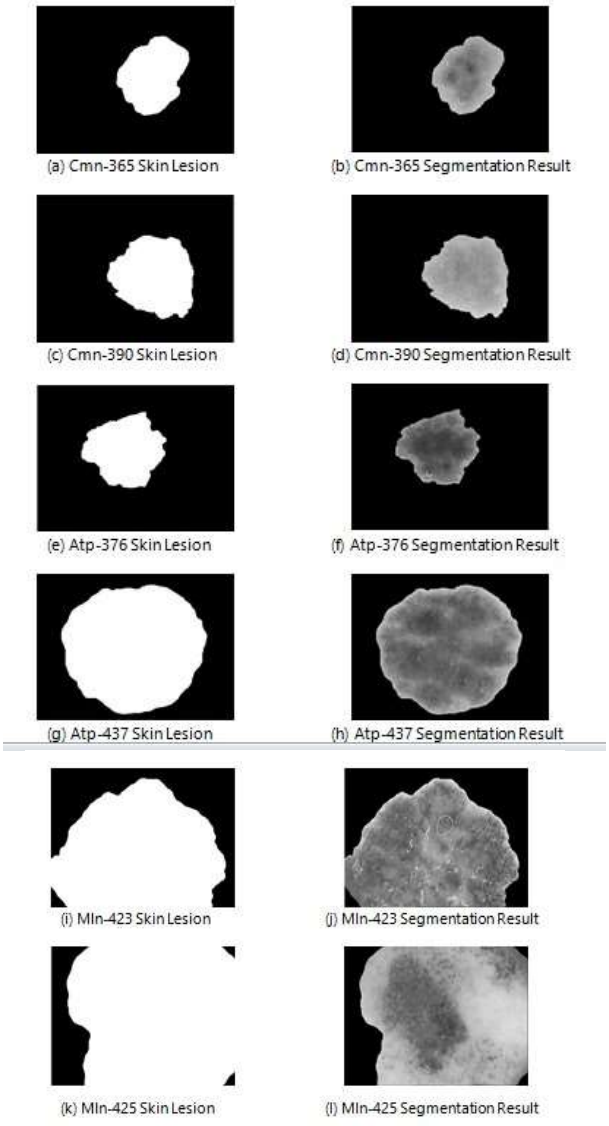


Figure 3. Skin Lesion Image and Segmentation Result Image

Matlab Program

The original image of dermoscopic RGB skin cancer with BMP format is inputted to the Matlab program that has been made. Figure 4 shows the Matlab program display for the original image input. After the original dermoscopic image is inputted into the program, then the image is converted to grayscale format. Figure 5 follows is the process of image changes at the grayscaling stage. The image that has been converted to grayscale format is processed by the Median Filter method to reduce noise. The Median filtering stage is seen in Figure 6. Figure 7 is the process of image input of skin lesions and image segmentation in the Matlab program

Figure 4. Dermoscopic Original Image Input

Figure 5. Grayscaling Process

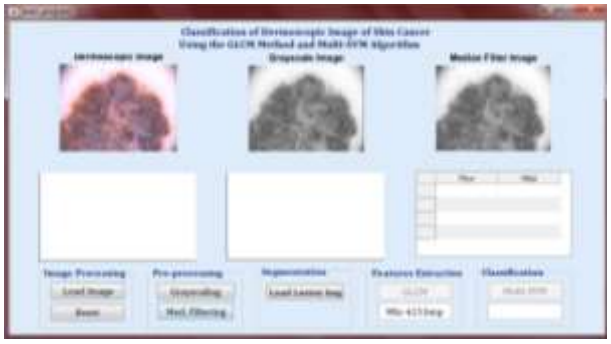


Figure 6. Median Filtering Process

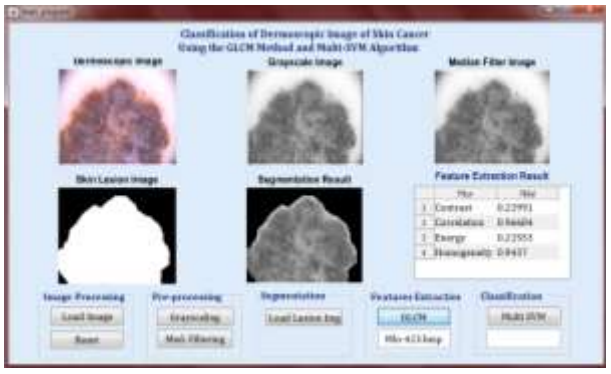


Figure 7. Input Process of Skin Lesion and Segmentation Process

Features Extraction

The feature extraction stage is performed using a GUI-based Matlab program. The GLCM method is used to retrieve image information based on texture features. The image of the segmentation process extracted using the GLCM method, the results show the values on 4 features, namely Contrast, Correlation, Energy and Homogeneity. The value of the GLCM features of each image, both the test image and the training image will be stored for processing at the classification stage. Figure 8 is the process of feature extraction in the Matlab program. The results of the feature extraction are recorded in Table 2.

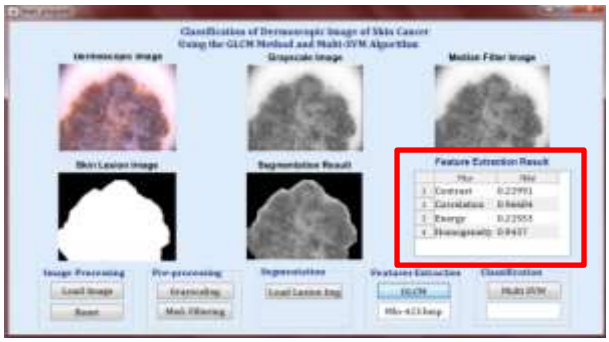


Figure 8. Feature Extraction Process

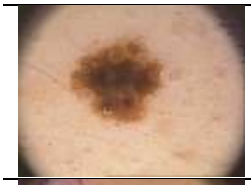
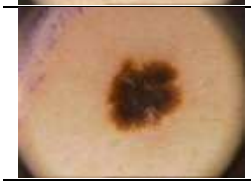
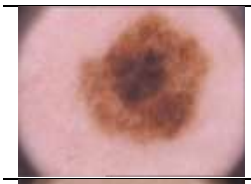
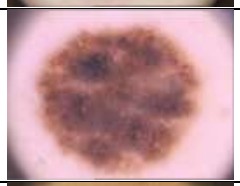
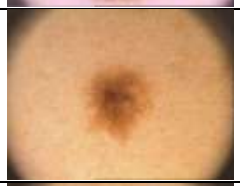
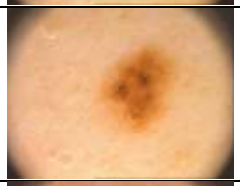
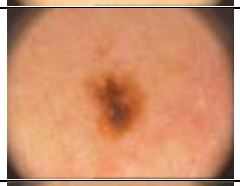
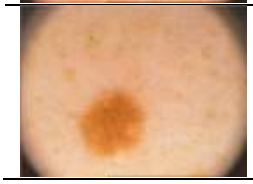
Table 2. Feature Extraction Results

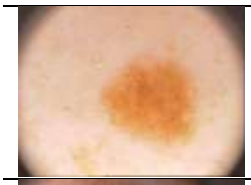
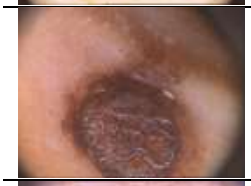
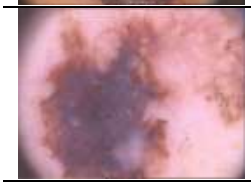
Image	Contrast	Correlation	Energy	Homogeneity
Atp-376	0,0578	0,9746	0,7283	0,9898
Atp-386	0,0415	0,9609	0,7749	0,9925
Atp-427	0,0889	0,9822	0,4757	0,9841
Atp-430	0,0645	0,9772	0,6573	0,9856
Atp-437	0,1449	0,9776	0,3179	0,9704
Cmn-364	0,0595	0,9831	0,7764	0,9915
Cmn-365	0,0544	0,9872	0,7560	0,9936
Cmn-374	0,0384	0,9814	0,8298	0,9947
Cmn-383	0,0508	0,9855	0,8094	0,9938
Cmn-390	0,0799	0,9882	0,6757	0,9894
Mln-418	0,1370	0,9631	0,2834	0,9595
Mln-420	0,1642	0,9815	0,1839	0,9712
Mln-423	0,2299	0,9668	0,2255	0,9437
Mln-424	0,2336	0,9456	0,1633	0,9378
Mln-425	0,1614	0,9785	0,1769	0,9659

Classification

The classification process is based on the GLCM feature values obtained at the feature extraction stage. The algorithm used is the Multi-SVM algorithm. The Matlab program for classification is shown in Figure 9. The results of the classification of 15 test images are recorded in Table 3.

Table 3. Classification Results

Dermoscopic Image	Image	Ground Truth	Classification Result
	Atp-376	Atypical Nevus	Atypical Nevus
	Atp-386	**Atypical Nevus**	**Common Nevus***
	Atp-427	Atypical Nevus	Atypical Nevus
	Atp-430	Atypical Nevus	Atypical Nevus
	Atp-437	**Atypical Nevus**	**Melanoma***
	Cmn-364	Common Nevus	Common Nevus
	Cmn-365	Common Nevus	Common Nevus
	Cmn-374	Common Nevus	Common Nevus
	Cmn-383	Common Nevus	Common Nevus

	Cmn-390	Common Nevus	Common Nevus
	Mln-418	Melanoma	Melanoma
	Mln-420	Melanoma	Melanoma

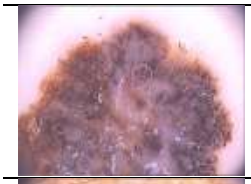
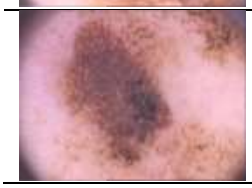
Dermoscopic Image	Image	Ground Truth	Classification Result
	Mln-423	Melanoma	Melanoma
	Mln-424	Melanoma	Melanoma
	Mln-425	Melanoma	Melanoma

Table 4. Confusion Matrix

Original Class		Prediction Class		
		a	***b***	***c***
a	Common Nevus	**5**	0	0
b	Atypical Nevus	1	**3**	1
c	Melanoma	0	0	**5**

Table 4 shows that the *Common Nevus* and Melanoma types do not have a misclassification of these types. While the Atypical Nevus types have 2 images which are classified into different types, namely 1 image to the Common Nevus type and 1 image to the Melanoma type. The percentage accuracy of dermoscopic image identification of skin cancer using the Multi-SVM algorithm in the testing data is calculated as follows:

$$\text{Percentage Accuracy} = \frac{\text{Amount of testing data identified correctly}}{\text{Total amount of testing data}} \times 100\%$$

$$= \frac{13}{15} \times 100\% = 86{,}67\%$$

A high accuracy value of 86.67% indicates that the proposed research method shows good classification results.

CONCLUSIONS

Current image processing techniques have been developed in the medical world to help doctors diagnose diseases more quickly. In this research, digital image processing is done to diagnose skin cancer by classifying dermoscopic images of skin cancer. The proposed method, the GLCM method and the Multi-SVM classification algorithm, can detect skin cancer with high accuracy, so it can be used to classify skin images as belonging to the Common Nevus, Atypical Nevus or Melanoma types. Further research can be done by developing a feature extraction and classification method using other methods so that better methods can be identified and compared in diagnosing skin cancer.

ACKNOWLEDGMENT

Thank you to Teresa Mendonca, Pedro M. Ferreira, Jorge S. Marques, Andre R. S. Marcal, and Jorge Rozeira from Pedro Hispano Hospital for the PH2 dataset used in this study.

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