Jurnal Teknik Informatika (JUTIF)
Vol. 5, No. 6, December 2024, pp. 1591-1598

DOI: https://doi.org/10.52436/1.jutif.2024.5.6.2514
p-ISSN: 2723-3863
e-ISSN: 2723-3871

COMBINATIONS OF FEATURE EXTRACTIONS AND MACHINE LEARNING ALGORITHMS FOR SKIN CANCER CLASSIFICATION

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(Article received: July 15, 2024; Revision: Auguts 14, 2024; published: December 29, 2024)

Abstract

One of the most common causes of death worldwide is skin cancer and its incidence is increasing. To achieve optimal treatment and improve clinical outcomes for patients, precision skin cancer detection and classification approaches are required, which can be achieved through the application of feature extraction and machine learning algorithms. The development of such algorithms to identify important patterns from skin cancer image datasets enables early detection and more accurate classification and more effective treatment. Although previous studies have tried to detect skin cancer using feature extraction techniques such as HFF, HOG, and GLCM, some weaknesses still need to be improved. This research aims to combine various feature extraction methods such as Gray Level Co-occurrence Matrix, Histogram Oriented Gradients, and Local Binary Patterns and machine learning algorithms such as Support Vector Machine, Random Forest, and Gaussian Naïve Bayes in the classification process between Melanoma and Nevus skin cancers. In this research, the number of datasets used is 17,397 derived from the ISIC Dataset. The results showed that the Histogram Oriented Gradients method with Support Vector Machine algorithm achieved the highest accuracy of 92%. The combination of Gray Level Co-occurrence Matrix and Local Binary Patterns with Random Forest algorithm also achieved an accuracy of 92%, the combination of Gray Level Co-occurrence Matrix, Histogram Oriented Gradients, and Local Binary Patterns with Random Forest algorithm also resulted in an accuracy of 92%. These findings suggest that the combination of various feature extraction methods and machine learning algorithms can improve accuracy in skin cancer classification, which in turn can contribute to early detection and more effective treatment.

Keywords: *Feature Extraction, Gray Level Co-occurrence Matrix, Histogram Oriented Gradients, Local Binary Patterns, Skin Cancer.*

1. INTRODUCTION

Cancer ranks as the leading cause of death and an obstacle to increasing life expectancy in all parts of the world [1]. According to the results of global cancer statistics (Global Cancer Incidence, Mortality and Prevalence [GLOBOCAN]), a prediction tool that estimates cancer incidence and mortality rates worldwide from the International Agency for Research on Cancer, there is an increasing trend in cancer incidence and mortality rates [2]. In this case, skin cancer is one of the most dangerous diseases found in the world after lung and breast cancer [3]. According to the World Health Organization (WHO), skin cancer is increasing yearly due to exposure to ultraviolet radiation from the sun that passes through the atmosphere and hits human skin [4], [5]. These skin cancers can affect both men and women in fair-skinned or light-skinned populations who bear the heaviest burden and are most commonly encountered, namely melanoma skin cancer and non-melanoma skin cancer [6]. There are three main causes of skin cancer: lifestyle, environmental, and genetic [7]. Skin cancer is one type of cancer that can be cured if treated early, but it can be fatal if not treated early and allowed to progress [8]. Therefore, doctors use the usual methodology to determine the type of skin cancer utilizing the asymmetry, border, color, and diameter (ABCD) technique to get an accurate classification based on the properties of skin lesions, but sometimes it is prone to measurement errors, so it is necessary to use the right techniques and algorithms, this requires an expert system that can classify the types of skin cancer [9], [10], [11]. Through the application of this technique, the speed of the detection process can be increased while minimizing human error and improving the quality of detection.

Seeja R D et al [12] have developed an algorithm using the Support Vector Machine (SVM) method to classify skin diseases that have been pre-trained using a dataset from ISBI 2016. Histogram-Oriented Gradient (HOG) as feature extraction on the dataset. The results of this study showed that the designed model obtained an accuracy of 85.19%. Recently, Abhijith L Kotian et al [13] proposed a melanoma detection technique using the SVM method in classification and GLCM as feature extraction on the ISIC dataset. The results of this study resulted in an accuracy of 83%. Siti Salbiah

Samsudin et al [14] proposed a classification method for seven types of skin lesions using images from the HAM10000 dataset. Multi-Resolution Empirical Mode Decomposition (MREMD) technique is used in this method to break the lesion image into several Bidimensional intrinsic mode functions (BIMF). Next, the Local binary pattern is applied to the ROI and BIMF. Artificial Neural Network (ANN) was used to classify and the results of this evaluation showed an accuracy of 98.9%. Research by Md. Mahbubur Rahman et al [15] used a hybrid feature extractor (HFF) which is used to combine two feature extraction approaches HOG, Local Binary Pattern (LBP), and Speed Up Robust Feature (SURF) into one feature vector. The proposed method achieves 99.85% accuracy. G. Neela Krishna Babu et al [16] proposed a skin cancer detection method based on SVM using a Histogram of Oriented Gradients feature extraction using images from the ISIC-2018 dataset, this study achieved an accuracy of 76%.

Although previous studies have tried to detect skin cancer using various feature extraction and classification techniques, there are still some weaknesses that need to be improved. Previous studies have used the SVM method with HFF, HOG, and Gray Level Co-occurrence Matrix (GLCM) feature extraction on various datasets such as ISBI 2016 and ISIC. However, they have not combined feature extraction methods with GLCM, HOG, and LBP methods. In addition, some studies have not tested the effectiveness of certain feature extraction methods using SVM, Random Forest (RF), and Gaussian Naïve Bayes (GNB) classification methods. Therefore, to test and combine the performance of various feature extraction and classification techniques in detecting skin cancer. This will help us gain a better understanding of which methods are most effective.

The main objective of this research is to combine each feature extraction to detect Melanoma and Nevus skin cancer, using GLCM, HOG, and LBP techniques, as well as using SVM, RF, and GNB classification methods. The results of this study can contribute to the development of accurate and reliable skin cancer detection. Benefits include improved early detection of skin cancer for professionals and the community.

2. RESEARCH METHODS

The method used to classify skin cancer consists of several stages, as described in Figure 1. The stages include preprocessing, feature extraction such as GLCM, HOG, and LBP, and classification using SVM, RF, and GNB. Figure 1 describes in detail the approach used in this study.

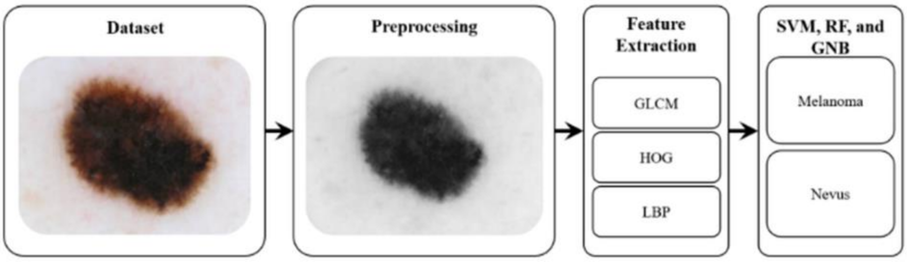

Figure 1. Research Architecture

2.1. Dataset

This article uses two types of lesions taken from the ISIC-2019 dataset [17], [18] namely Melanoma (MEL) and Nevus (NV). There were 12875 images of Melanoma lesions, which is a malignant type of skin cancer and 4522 images of Nevus lesions, which is a common type of mole. An attempt was made to prevent imbalance in the dataset as there is a significant difference in the amount of data between the two lesion types. Therefore, the SMOTE (Synthetic Minority Over-sampling Techinique) oversampling method was used. This method can effectively increase the sample size of nevus lesions to a level comparable to that of Melanoma lesions.

2.2. Dataset

Medical datasets have various kinds of noise caused by lighting, markings, light contrast, etc. [19]. This can reduce the accuracy obtained from training data processed by classification, so noise such as hair around skin lesions must be removed using the inpaint technique. After removing hair, RGB is converted to Grayscale and performs Median filtering which has a special function in the medical field to remove noise from the image used [20]. This method collects pixel values from the image, follows them ascending, and the center value is taken instead of the pixel value. This model is defined by equation 1.

$$y_{(m,n)} = median\{x_{(i,j)}, (i,j) \in \mathrm{C}\} \quad (1)$$

Where $y_{(m,n)}$ is the output and C represents the neighborhood of the surrounding values. In this study, median filtering removes noise in skin cancer images by using a $5 \, x \, 5$ filter mask.

2.3. Feature Extraction

Feature extraction is an important part of this research to help identify objects from the dataset used. This process is used to obtain a representation of the image that is converted to numeric while the important information is not changed [21], [22]. Feature selection can be significant for improving accuracy [23]. In this study, three feature extractions are used to help identify skin cancer, namely GLCM, HOG, and LBP.

2.4. Gray Level Co-occurrence Matrix

The Gray Level Co-occurrence Matrix (GLCM) feature extraction technique is used to determine a particular gray level with another gray level [24]. The GLCM method identifies perceptual relationships between pixels in an image [25]. GLCM itself records the frequency of occurrence of a pair of pixel values with a predetermined distance and direction for each pair of pixels. There are several features used in this research including:

1. Contrast measures the intensity of a pixel and its neighbors. Equation 2 contrast:

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

2. Correlation is the combination of pixels with image neighbors. Equation 3 correlation:

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (3)$$

3. Energy is known as diversity. It is the sum of the squared components of the GLCM. Equation 4:

$$Energy = \sum_{i,j=0}^{N-1} \left(P_{ij}\right)_2 \quad (4)$$

4. Homegenity indicates the similarity between pixels in an image. Equation 5 homogeneity:

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (5)$$

2.5. Histogram of Oriented Gradients

Histogram of Oriented Gradients (HOG) was first introduced by Dalal and Triggs for pedestrian detection [26]. HOG has gained significant attention from the computer vision and pattern recognition communities and has been widely used in various applications such as face recognition, image retrieval, and disease diagnosis [27]. This approach has proven to be a simple and effective way to describe the visual attributes and characteristics inherent in objects.

HOG differs from traditional feature descriptors in that it operates on local image cells. HOG features are generated by calculating the gradient for each pixel in the image, including its magnitude and orientation [28], thus providing features that distinguish objects from variations in lighting and background noise, making them effective descriptors [24].

2.6. Local Binary Patterns

Local Binary Patterns (LBP) is a feature extraction used for image management and pattern recognition. This method obtains robust texture descriptors that are not affected by different lighting and distribution [14]. LBP assigns binary labels 0 and 1 to align pixels in an image according to a certain threshold calculated from the values of neighboring pixels around the central pixel [15], [29]. If the neighboring value is larger than the center value, a value of 1 is assigned, whereas if the neighboring value is smaller than the center value, a value of 0 is assigned [30]. In addition, LBP is simpler and more effective to use Equation 6:

$$LBP\ (x_c, y_c)_{R,P} = \sum_{P=0}^{P-1} s\left(g_p - g_c\right)2^p \quad (6)$$

Where g_c is the center pixel value, g_p is the neighbor pixel value, R is the radius value, and P is the neighbor value.

2.7. Support Vector Machine

Support Vector Machine (SVM) is a machine learning technique for classification and regression problems that has been proposed by Vapnik et al [31], [32]. SVM classification has the characteristics of high precision, good generalization ability, and good robustness in a collection of small data sets, as well as classification of non-linear features [33]. The SVM work process consists of creating a model that has the ability to separate two different classes by creating a hyperplane that has the maximum margin between the classes. can be seen with equation 7.

$$f(x) = w^T x + b \quad (7)$$

Where w is the minimum weight, c is the classification data value and b is the linear coefficient estimated from the training data.

2.8. Random Forest

Random forest (RF) is one of the best-performing algorithms [34]. This random forest model combines a number of data samples and a randomly selected number of inputs [35]. This method is fast and flexible and is suitable for regression and classification [36]. This algorithm uses voting from multiple decision trees that have been randomly trained on a subset of characterizations to reduce overfitting and improve model generation [37]. This algorithm can also support large datasets, overcome noise, and outliers, and have high accuracy. Equation 8 can be seen below.

$$Gini = 1 - \sum_{i=1}^{C}(p_i)^2 \quad (8)$$

Where c is the number of classes in the data and p_i is the probability of occurrence of the value i in the class.

2.9. Gaussian Naïve Bayes

Gaussian Naïve Bayes (GNB), one of the variants of the Naïve Bayes algorithm calculated using normal distribution and derived from Bayes' theorem, one of the efficient classifiers [38], [39]. This method is known for its simple approach and handles binary or categorical input values and does not require a large amount of data for training [40]. It is a good choice that solves the height problem and produces fairly accurate results. The following equation 9 can be seen.

$$P(x = v|C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{\frac{-(v-\mu_k)^2}{2\sigma_k^2}} \tag{9}$$

Where c is an attribute in the classification, C_k is the label of the class, μ_k is the average of related to C_k, and σ_k is a measure of the variance of data within one class.

3. RESULTS AND DISCUSSION

In this section, various experimental steps to combine feature extraction are applied and ensure the classification of skin cancers including Melanoma and Nevus. In this study, 17.397 skin cancers consisting of Melanoma 4.522 images and Nevus 12.875 images were used. The dataset is not balanced between the two to equalize it has been used oversampling, as shown in Figure 2.

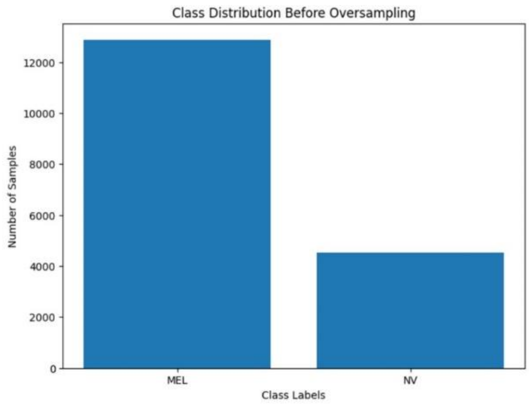

Figure 1. Dataset before oversampling

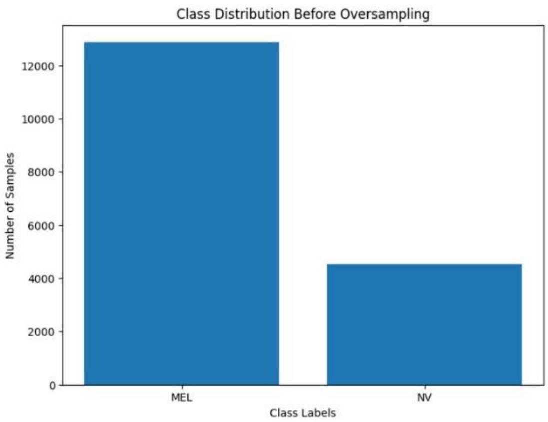

Figure 2. Dataset after oversampling

In testing the GLCM, HOG, and LBP feature extraction models are tested through the classification process using SVM, RF, and GNB to measure accuracy, precision, and F1-score on Melanoma and Nevus datasets. To evaluate this performance, the dataset was divided into two parts 80% training data and 20% test data. Table 1 shows the numerical results of the extracted features. Figure 4 presents the images of each feature extraction using the SVM classification approach.

Based on the test results that have been carried out with the applied method and compared with previous research as in Table 1 in melanoma and nevus skin cancer classification research which produces 72% GLCM accuracy, 85% HOG, and 74% LBP of the original dataset using SVM classification. So that the best results that have been tested and adjusted to all datasets that have been obtained are with the HOG method as shown in Table 1 and Figure 4.

Table 1. Support Vector Machine Classification Results

Feature Extraction	Support Vector Machine		
	Accuracy	precision	F1 Score
GLCM	72%	72%	72%
HOG	85%	85%	85%
GNB	74%	75%	74%

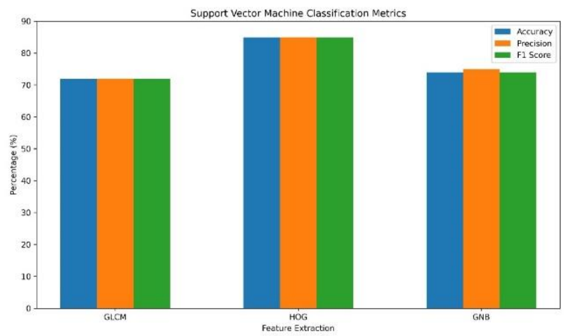

Figure 3. Support Vector Machine Classification Visualization

Table 2 shows the results of the comparison of the accuracy of melanoma and nevus skin cancer classification with RF classification applied to datasets that have been processed with GLCM, HOG, and LBP. The test results show that the HOG method has the highest accuracy of 92%. However, it should be noted that the GLCM method also gave an accuracy of 77%, while the LBP method had a slightly lower accuracy of 72%. Although the HOG method gave the best results, the feature extraction comparison can provide additional and important information for skin cancer classification.

Table 2. Random Forest Classification Results

Feature Extraction	Random Forest		
	Accuracy	precision	F1 Score
GLCM	77%	77%	76%
HOG	92%	92%	92%
GNB	72%	72%	71%

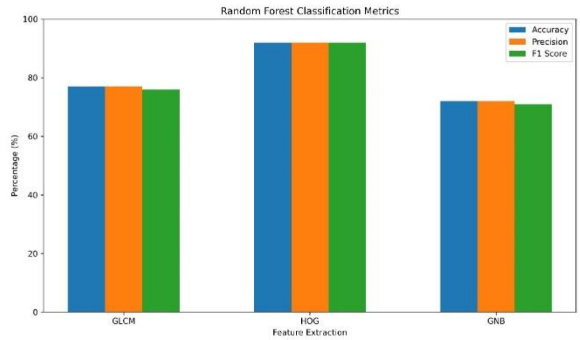

Figure 4. Random Forest Classification Visualization

In the test results of Table 3, the performance of the GLCM, HOG, and LBP methods was analyzed using GNB classification. The results of this test show that the HOG method still gives the highest accuracy in other extraction methods, which is 64%. The GLCM method shows accuracy, which is 64%. But the LBP method still shows lower accuracy than other methods, which is 62%.

Table 3. Gaussian Naïve Bayes Classification Results

Feature Extraction	Gausian Naïve Bayes		
	Accuracy	**precision**	**F1 Score**
GLCM	64%	69%	61%
HOG	63%	64%	63%
GNB	62%	63%	61%

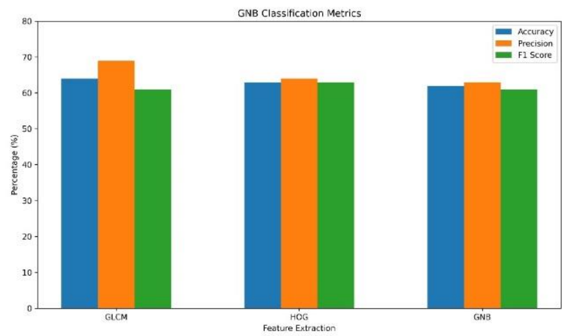

Figure 5. Gaussian Naïve Bayes Classification Visualization

It can be seen in Table 4 and Figure 7 that the test results obtained the highest accuracy using a combination of feature extraction, namely, GLCM, LBP and GLCM, HOG, LBP with RF classification, which is 92%. This shows that the combination of different feature extraction methods into one vector can improve accuracy in this study.

Table 4. Combination Feature Extraction

Feature Extraction	Feature Extraction Combination		
	SVM	**RF**	**GNB**
GLCM, HOG	78%	80%	71%
GLCM, LBP	89%	92%	61%
HOG, LBP	79%	78%	71%
GLCM, HOG, LBP	87%	92%	62%

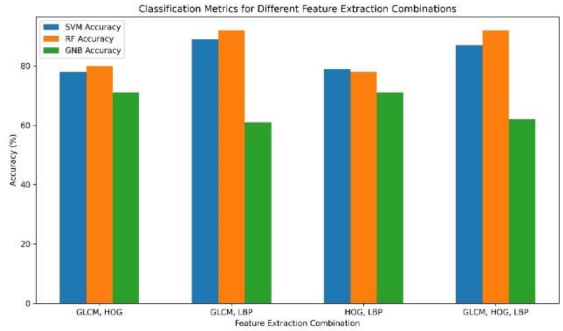

Figure 6. Feature Extraction Combination

4. DISCUSSION

Based on the research findings, great efforts have been made to categorize skin cancers including melanoma and nevus using a series of feature extraction and classification techniques. Although the HOG method achieved the highest classification accuracy using SVM and RF algorithms, the combination of GLCM, HOG, and LBP feature extraction also achieved high accuracy for RF classification.

It can be seen from Table 5 of the above comparison that this research can achieve higher accuracy (92%) than the research of Seeja R D et al [12] using the HOG method of the SVM algorithm. conducted research that achieved an accuracy of 85.19%. Furthermore, Md. Mahbubur Rahman et al [15] achieved a high accuracy of 99.85% using a combination of HOG, LBP, and SURF. The results of research that combines GLCM, HOG, and LBP with the random forest algorithm also provide competitive results with 92% accuracy.

Table 5. Comparison of methods

Authors	Feature extraction	Machine learning	Accuracy
Seeja R D et al [12]	HOG	SVM	85.19%
Abhijith L Kotian et al [13]	GLCM	SVM	82%
Siti Salbiah Samsudin et al [14]	LBP, MREMD	ANN	98.9%
Md. Mahbubur Rahman et al [15]	HOG, LBP, SUFT	HFF	99.85%
G. Neela Krishna Babu et al [16]	HOG	SVM	76%
Proposed Method	HOG	SVM	92%
Proposed Method	GCLM, HOG, LBP	RF	92%
Proposed Method	GLCM, LBP	RF	92%

However, this research shows a combination of more complex feature extraction methods, such as the one conducted by Md. Mahbubur Rahman et al. Can result in higher accuracy. Therefore, further research can be focused on using a combination of more complex feature extraction methods and testing with various datasets to improve classification accuracy.

This study did not use image segmentation that distinguishes it from other skin lesions, there is still room to achieve better accuracy requiring a more sophisticated approach in feature extraction or selection of the correct and appropriate classification algorithm. These results make an important contribution to the future development of skin cancer classification and we hope that it will be useful for doctors and patients in detecting skin cancer.

5. CONCLUSION

The results of this study prove that by combining several feature extraction methods and machine learning algorithms have been able to identify melanoma and nevus skin cancers accurately. The final results show that HOG produces the highest accuracy, reaching 92%. The combination of GLCM & HOG, and GLCM & HOG & LBP feature extraction also obtained the same accuracy of 92%. HOG proved to provide the best aaccuracy results, and the combination of GLCM, HOG, and LBP features has the potential to further improve skin cancer detection performance. This finding shows that the combination of GLCM, HOG, and LBP feature extraction is capable of matching the accuracy obtained from the HOG method alone.

ACKNOWLEDGMENT

The researcher would like to thank the laboratory of the Faculty of Computer Science, Universitas Muslim Indonesia for the facilities provided, as well as the lecturers for their support and assistance in carrying out this research.

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