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Image Segmentation Using Hybrid Clustering Algorithms for Machine Learning-Based Skin Cancer Identification

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ABSTRACT

Early identification of skin cancer is crucial to increasing the chances of a cure and reducing mortality rates. This research aims to develop a method for identifying skin cancer using image processing techniques, specifically the hybrid clustering method. This method integrates machine learning with fuzzy c-means clustering (FCM) and hierarchical clustering (HC) segmentation techniques to segment skin cancer more accurately. Hybrid clustering is used to separate suspicious areas in skin images, resulting in more precise segmentation compared to conventional methods. The segmentation results are then used as input for various machine learning methods that are trained to recognize patterns in identifying types of skin cancer. Tests were carried out using data obtained from the Kaggle Dataset, and the results showed that the proposed method was able to achieve a high level of accuracy in identifying skin cancer. After segmentation, the ensemble learning method yielded the best identification results. The Random Forest algorithm, which is applied to process and analyze features from skin images, shows higher performance compared to other machine learning methods. Tests show that the Random Forest method with the proposed segmentation achieves an accuracy level of up to 89%, while other machine learning methods such as K-Nearest Neighbor only achieve an accuracy level of around 86%. This research makes an important contribution to the development of efficient and reliable diagnostic tools for skin cancer identification, with appropriate segmentation methods proven to increase accuracy.

Keyword: Identification of Skin Cancer; Machine Learning; Hybrid Clustering; Fuzzy C-Means Clustering; Hierarchical Clustering.

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1. INTRODUCTION

One of the most common cancers, skin cancer, can be deadly if not diagnosed and treated early. Although early detection of skin cancer can increase the chances of a cure, the diagnosis process often requires a detailed medical examination and a significant amount of time (Mamun & Uddin, 2021). With an increasing incidence of skin cancer, low awareness among the growing population, and a lack of adequate clinical expertise and services, there is an urgent need for AI systems to assist clinicians in this domain (Goyal et al., 2020). Machine learning-based methods, a branch of AI, have demonstrated significant potential in aiding in the early detection of various diseases, including skin cancer. Machine learning technology enables data analysis at scale and can identify complex patterns that human inspection might miss.

Previous research has shown the effectiveness of using machine learning methods in the process of identifying skin cancer. The use of Gray Level Co-occurrence Matrix (GLCM) and statistical features allows effective classification of various types of skin diseases, with Support Vector Machine (SVM) slightly superior to other methods such as Decision Tree (DT) and K-Nearest Neighbor (KNN) (Ahammed et al., 2022). Other research has developed a skin disease diagnosis system based on CNN and SVM that is integrated into an Android mobile application, providing a diagnosis solution that is faster, more accurate, and easier to access for users (Elngar et al., 2021). As a result, the methods used in previous studies have made significant contributions to the field of skin cancer identification, highlighting the urgent need for more sophisticated and accurate diagnostic tools to assist clinicians in the early diagnosis of skin cancer.

However, there are various significant obstacles in the process of identifying skin cancer. One obstacle is segmentation, where there are significant challenges such as variations in lighting, various skin colors from different ethnic groups, and others (Islam et al., 2024). In the context of skin cancer, image segmentation is an important step that allows identification of suspicious skin areas. Across races and individuals, skin color differences are large. Therefore, finding and identifying skin color in images requires a higher level of precision and confidence (Saber Iraji & Tosinia, 2012). Research using FCM techniques for segmentation and SVM for skin cancer classification resulted in clear and sharp images, thereby improving the performance of the algorithm being built. Another study proposed an ensemble model of CNN and transformers, which showed superior performance compared to using traditional algorithms in the process of identifying skin cancer (Nanni et al., 2023). Apart from that, research using fuzzy c-means clustering techniques for image segmentation and various feature extraction methods such as Local Binary Pattern (LBP), RGB color space, and Gray Level Co-occurrence Matrix (GLCM), as well as classification with the Convolutional Neural Network (CNN) and the differential evolution (DE) algorithm, succeeded in achieving a detection accuracy rate of 91% using a dataset of skin cancer images. These results show significant progress compared with traditional methods (Burada et al., 2024).

Based on previous research, image segmentation is still an important part of this process. However, the fuzzy c-means (FCM) method has several weaknesses that affect segmentation accuracy. Fuzzy c-means clustering is generally used for image segmentation, which allows pixels to be classified into one or more clusters according to their membership values. However, this clustering method still has problems related to shifting cluster centers and sensitivity to overlapping intensity distributions between classes (Fariza et al., 2019). Furthermore, FCM necessitates the initial establishment of the anticipated number of clusters in the image, a task that proves challenging in the context of skin cancer identification due to the significant variations in the shape, size, and color of skin lesions. Variations in lighting and skin color between individuals can also influence the accuracy of FCM segmentation (Dhal et al., 2023). In this context, the importance of more accurate and reliable segmentation methods, such as hybrid clustering, becomes very clear. Hybrid clustering is able to separate suspicious areas in skin images with more precision, thereby improving the quality of input for machine learning algorithms.

The hybrid clustering method is a segmentation technique that can increase the accuracy of separating cancerous areas from normal skin. This technique improves the limitations of conventional clustering methods by producing more precise and clear segmentation, which can then be used as input for machine learning models. Research on combining the fuzzy c-means algorithm with other methods produces an effective and robust segmentation approach for skin lesion images, where the proposed method improves the accuracy and reliability of skin cancer detection systems (Masood & Al-Jumaily, 2013). Another study tested a fuzzy logic-based image segmentation model together with a modified deep learning model for skin cancer detection, where there was dermoscopic image enhancement using pre-processing techniques, mathematical logic infusion, standard deviation methods, and L-R fuzzy defuzzification methods to improve segmentation results (Singh et al., 2023).

In this study, we propose a method for identifying skin cancer using several clustering algorithms. Hybrid clustering is used for skin image segmentation, which produces a visual representation of suspicious areas. The segmentation results are then analyzed by a machine-learning algorithm to determine whether skin cancer is present. This method integrates two main concepts: the fuzzy c-means (FCM) clustering segmentation and the hierarchical clustering (HC) method. The FCM-HC technique is used to more accurately separate suspicious areas in skin images. In this context, segmentation methods have been enriched by using a combination of both methods to determine optimal cluster areas and ensure that segmentation is carried out accurately. Combining these segmentation techniques allows for more accurate detection of skin cancer.

In addition, this research also involves testing the performance of various identification methods using machine learning. In this test, various machine learning algorithms were evaluated to determine their ability to recognize patterns and identify types of skin cancer. The identification methods tested include Decision Tree (DT), K-Nearest Neighbor (KNN), Random Forest (RF), Logistic Regression (LR), and Naïve Bayes (NB). It is hoped that the results of this test will provide a better understanding of the advantages and disadvantages of each identification method, as well as enable the selection of the most suitable method for use in a particular situation. Thus, this research not only contributes to the development of better skin cancer detection techniques, but also helps guide the practical use of identification methods in the clinical setting. With increasing accuracy and efficiency in early detection of skin cancer, it is hoped that this research can contribute significantly to efforts to prevent and treat this disease through the development of more sophisticated and accurate diagnostic.

2. RESEARCH METHOD

This section will explain the methodology used in research to identify skin cancer using machine learning-based hybrid clustering segmentation. The proposed research's systematic steps can be seen in Figure 1 below.

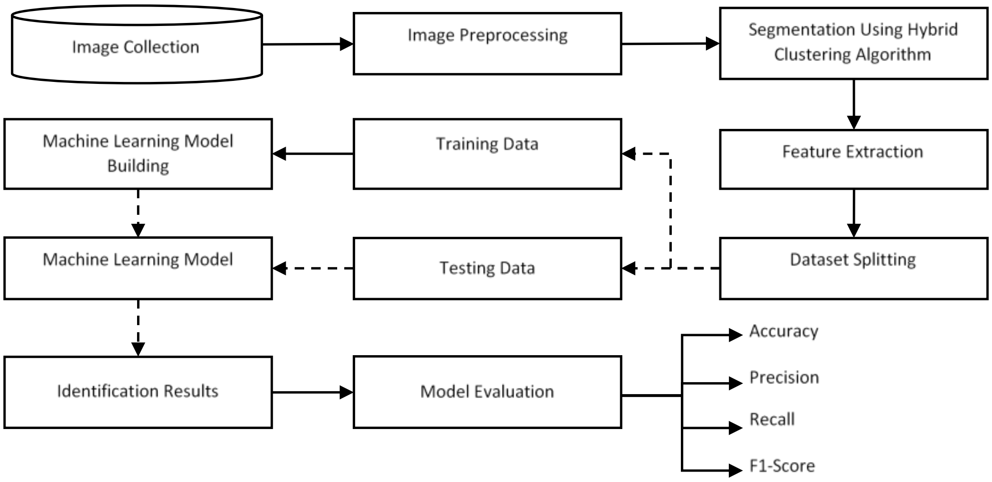
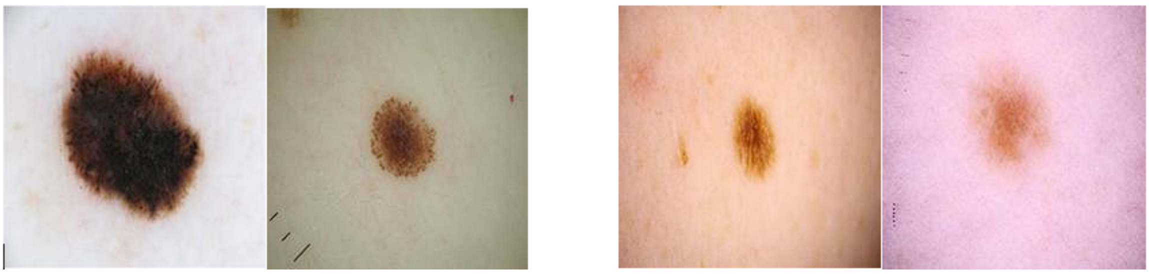


Fig 1. Research Steps with the Proposed Method

According to Figure 1, each step can be described as follows:

2.1 Image Collection

The data used in this research was obtained from the Kaggle Dataset with the name Skin Cancer, with a total of 2000 images of two types of skin cancer, namely Malignant and Benign. Figure 2 below shows several images of the types of skin cancer used in research.



(a) (b)

Fig 2. Types of Skin Cancer Disease
(a) Malignant, (b) Benign

In this research, dividing the dataset into two parts, namely training data and testing data, is a crucial step in the experimental process. It is crucial that the model being developed can generalize patterns from previously studied data to new data. To avoid bias in data selection, the typical proportions are 70% for training and 30% for testing, but this can vary depending on problem complexity and data availability. This ensures that both subsets have a uniform distribution of the desired classes or features. Training data is used to train the model, whereas testing data is used to test the trained model's performance. This process allows researchers to evaluate how well a model can generalize patterns from never-before-seen data.

2.2 Image Preprocesing

The preprocessing process on skin images aims to remove noise and improve image quality (Hoshyar et al., 2014). The first step is to convert the image from the RGB color space to another color space more suitable for analysis, such as HSV or YCbCr. Next, to reduce noise in the image, a smoothing filter such as Gaussian blur is used. After the noise has been successfully reduced, image sharpening techniques are applied to clarify edges and important details in the image. Additionally, image contrast enhancement can be done using techniques such as histogram equalization to improve the visibility of details.

2.3 Hybrid Clustering

Hybrid clustering segmentation for skin images is performed by setting parameters according to the image's needs and characteristics, similar to clustering methods in general. The segmentation process on all images will be carried out to obtain a visual representation of suspicious areas in each image and find parts of the skin infected with cancer. The steps taken in the segmentation process using the proposed method can be seen in Figure 3, as follows:

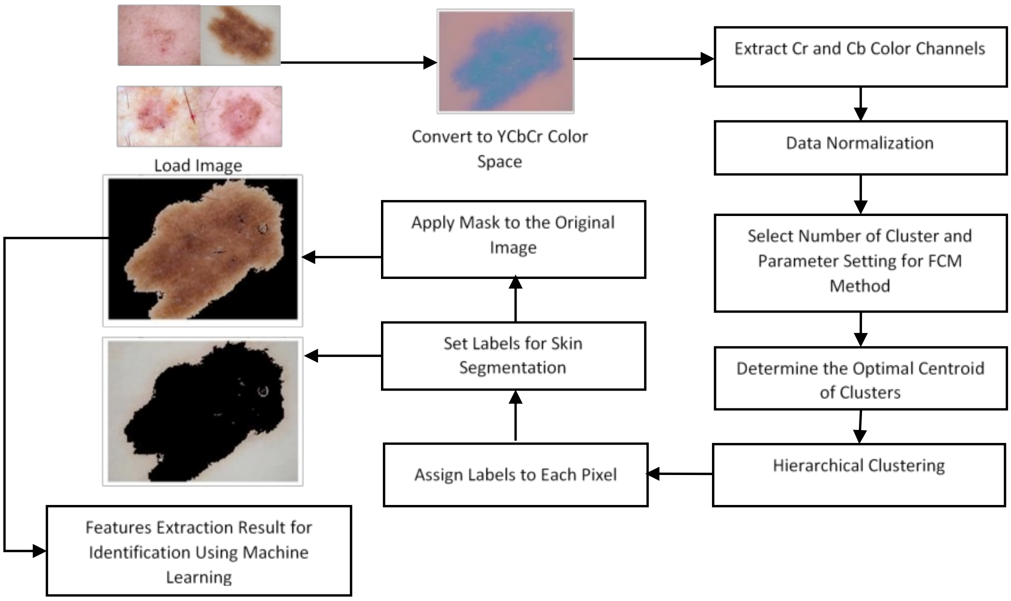


Fig 3. Segmentation Process Uses the Hybrid Clustering Method

After carrying out image processing and setting other parameters, the next step is to segment the image to find areas of skin infected with cancer. First, each image will be processed using the fuzzy c-means (FCM) algorithm to determine the cluster centroid. This is done by taking into account the degree of membership of each pixel to the resulting cluster, so that each image has as many centroids as the specified clusters and has a label that corresponds to the nearest cluster. Each resulting centroid is then used as the initial input for the hierarchical clustering (HC) method. Next, the HC process is used to more accurately identify parts of the skin infected with cancer. The FCM result label helps to determine the initial grouping that will be refined through HC. In this stage, the clusters that have been formed are sorted hierarchically to clarify the boundaries between healthy and infected areas. Labels representing infected skin areas are typically chosen based on clustering analysis results. In this way, healthy skin areas can be separated and retained as parts of the image infected with cancer during the segmentation process. This process aids in pinpointing the areas of skin that require further medical attention.

2.4 Features Extraction

After the image segmentation stage is carried out, the next step is to extract relevant features from each area of the segmentation results. These features include various visual aspects of the image that can be used to differentiate between cancerous areas and normal skin. One commonly used feature is the Histogram of Oriented Gradients (HOG), which describes image texture by calculating the orientation pattern based on the brightness gradient of pixels in a neighboring window (Carcagnì et al., 2015). To obtain feature values using the HOG method, equations 1 and 2 can be used as follows (Anggraeny et al., 2020):

$$M(i,j) = \sqrt{(I_x(i,j))^2 + (I_y(i,j))^2} \quad (1)$$

$$\theta(i,j) = arctan\left(\frac{I_y(i,j)}{I_x(i,j)}\right) \quad (2)$$

For each pixel in the image, the magnitude gradient (M) and orientation gradient (θ) can be calculated using the Sobel operator or other operators. After that, the image is divided into small cells, whose orientation gradient histogram is then calculated (Cheon et al., 2011). Equation 3 is used to normalize the histogram, reducing the influence of light or contrast.

$$v_{i,j,k} = \frac{\sum_p \sum_q M(p,q).bin(p,q,i,j,k)}{\sqrt{\sum_p \sum_q M(p,q)^2}} \quad (3)$$

Where $v_{i,j,k}$ are normalized voxel values, *bin(p,q,i,j,k)* is the gradient orientation histogram in cell k at position *(i,j)*, and $\sum p \sum q M(p,q)^2$ is the sum of the squares of the gradient magnitudes in that cell.

Apart from that, this research also carried out extraction using the HSV method, which is often used to extract color information from images. The HSV (Hue-Saturation-Value) color model is a color system that describes colors based on the attributes hue, saturation, and value (Islami, 2021). In general, color conversion from RGB to HSV can be done using equations 4, 5, and 6 (Kurniastuti et al., 2022):

$$V = max(RGB) \quad (4)$$

$$S = \begin{cases} \frac{v-min\,(R,G,B)}{V}, if\ V \neq 0 \\ 0, if\ V = 0 \end{cases} \quad (5)$$

$$H = \begin{cases} \frac{60(G-B)}{(V-min(R,G,B))}, if\ V = R \\ 120 + \frac{60(B-R)}{(V-min(R,G,B))}, if\ V = G \\ 120 + \frac{60(R-G)}{(V-min(R,G,B))}, if\ V = B \end{cases} \quad (6)$$

The variables R, G, and B represent the red, green, and blue intensity values of the pixel, measured in the range 0 to 255, respectively; V represents the value (brightness value) in the same range; S represents the saturation value in the range 0 to 1, and H represents the hue value (color value) in degrees, generally in the range 0 to 360.

2.5 Machine Learning Models

Machine learning is a process that uses computational techniques to build a model that can learn from data and make predictions or decisions without being explicitly programmed (Sharma & Chaudhary, 2023). These models allow computers to “learn” from patterns in the data they are given and then use the knowledge gained to make predictions or make decisions about new data. This process involves several steps, including data processing, model selection, model training, model validation, and hyperparameter tuning. These steps aim to ensure that the resulting model can produce accurate and reliable predictions or decisions when applied to new data.

Machine learning model building has become an integral part of many modern applications, from data analysis to pattern recognition, image processing, and even decision-making in artificial intelligence. With their ability to process and understand data efficiently, machine learning models enable us to extract new insights from complex and diverse data. In this study, various machine learning algorithms were used and evaluated to determine their ability to recognize patterns and identify types of skin cancer. The identification methods tested include Decision Tree (DT), K-Nearest Neighbor (KNN), Random Forest (RF), Logistic Regression (LR), and Naïve Bayes (NB).

2.6 Models Evaluation

After training the model using training data, the next step is to evaluate its performance using previously defined testing data. This evaluation is important to ensure the reliability and quality of the skin cancer identification system being developed. At this stage, model performance is evaluated using various relevant metrics to measure the extent to which the system is able to perform its tasks well, such as accuracy, precision, recall, and the F1-score to evaluate model performance (Tahyudin et al., 2024).

Accuracy is used to measure how many predictions are correct out of all the predictions made by the model using equation 7.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

Precision is used to measure how many true positive results there are out of all the results predicted as positive by the model using equation 8.

$$Presicion = \frac{TP}{TP+FP} \quad (8)$$

Recall is used to measure how many true positive results the model can identify from all the true positive results in the dataset, using equation 9.

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

F1-score is the harmonic average of precision and recall, which provides a balance between the two metrics using equation 10.

$$F1 - Score = 2 \text{ x } \frac{Precision \text{ x } Recall}{Precision+Recall} \quad (10)$$

Where:
TP : True Positive
TN : True Negative
FP : False Positive
FN : False Negatif.

3. RESULTS AND DISCUSSION

This research aims to develop a method for identifying skin cancer using machine learning and hybrid clustering. By utilizing machine learning technology and image segmentation, this research succeeded in developing an approach that can help in the more accurate early detection of skin cancer. Based on the research results obtained, there are several results that can be explained as follows:

3.1 Segmentation Results

In general, the segmentation process using ordinary clustering methods, such as fuzzy c-means, involves several steps aimed at dividing the image into several homogeneous clusters. First, initialization is carried out, where the initial cluster centers are randomly assigned. Next, each pixel in the image is assigned a degree of membership for each cluster. This degree of membership determines how close or how far the pixel is from the cluster center. The next step is the calculation of a new cluster center, which is calculated based on the membership degree of each pixel. This new cluster center is the center point of the cluster, which is adjusted based on the contribution of each pixel. Iteration is carried out by repeating the steps of calculating membership degrees and new cluster centers until the convergence criteria are met, usually when the change in cluster center values between two consecutive iterations is very small. Once convergence is achieved, each pixel is labeled based on the cluster that has the highest degree of membership, resulting in image segmentation in which each pixel is classified into one of the clusters. For example, the results of image clusters using the FCM method can be seen in Figure 4 below.

Fig 4. Segmentation Using the FCM Method

In this research, we apply skin cancer image segmentation using a hybrid clustering method that combines fuzzy c-means (FCM) and hierarchical clustering (HC). Although FCM is often effective in many cases, it has several drawbacks. First, FCM is very sensitive to poor initialization, which can lead to convergence to a non-optimal solution. Second, FCM tends to be sensitive to noise in the image, which can result in inaccurate segmentation. Finally, because it requires quite a lot of computation, FCM performance can be slow, especially on large images or with a large number of clusters. The segmentation process with the proposed hybrid clustering begins with the application of FCM to provide initial settings for hierarchical clustering.

The first step is to randomly select the initial cluster centers or use a specific initialization method. After initialization, each pixel is assigned a membership degree to each cluster based on the FCM results. This iterative FCM process updates the cluster centers by considering each pixel's membership degree and continues until the convergence criterion is met. After the initial segmentation with FCM is complete, the results are used as input for the hierarchical clustering method. Hierarchical clustering then groups the data that has been processed by FCM, improving the clustering structure based on hierarchical relationships between the data. This helps overcome some of the weaknesses of FCM, such as sensitivity to noise and poor initialization, by improving global data clustering. Iteration in hierarchical clustering allows further adjustments to the clusters formed, improving the accuracy of the final segmentation. The last step is to label each pixel based on the cluster that this combination process finds. The label is based on the cluster with the highest membership degree from the hierarchical clustering results. The segmentation results using the hybrid clustering method can be seen in Figure 5 below.

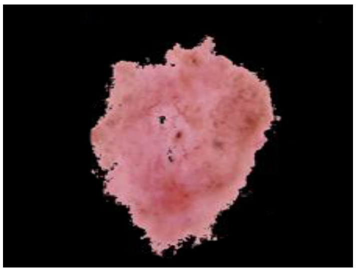


Fig 5. Segmentation using the Hybrid Clustering Method

By combining the strengths of fuzzy c-means (FCM) clustering and hierarchical clustering (HC), this hybrid method aims to overcome the shortcomings of each method and produce segmentation that is more accurate and robust against noise.

3.2 Identification Results

After the hybrid clustering process, the results of identifying skin cancer using machine learning methods produce more accurate and detailed segmentation compared to traditional methods. The first step in this process is skin image segmentation using hybrid clustering, in which each image forms clusters according to pixel proximity. After that, relevant features are extracted from each segmentation region, such as texture and color. These features are then used as input for machine learning models, such as classification algorithms. The machine learning model is trained using a labeled dataset, which includes information about whether the skin area has cancer or not.

Once the training process is complete, the model can be used to classify new skin regions based on the extracted features. The results of identifying skin cancer are expressed in the form of a label, for example, “Malignant” or “Benign,” which indicates the presence or absence of skin cancer in each area of the image observed. Thus, the machine learning method after the segmentation process allows for more precise and accurate identification in detecting the presence of skin cancer in the analyzed skin images. In Table 1, you can see the performance results of several algorithms used to identify skin cancer before the segmentation process is carried out.

Table 1. Skin Cancer Identification Using Machine Learning Methods without Segmentation

Methods	Performance Methods			
	Accuracy	Precision	Recall	F1-Score
Decision Tree (DT)	0.7600	0.7657	0.7600	0.7587
K-Nearest Neighbor (KNN)	0.8250	0.8251	0.8250	0.8249
Random Forest (RF)	0.8533	0.8642	0.8533	0.8522
Logistic Regression (LR)	0.7933	0.8010	0.7933	0.7920
Naïve Bayes (NB)	0.6250	0.7569	0.6250	0.5697

Prior to the hybrid clustering segmentation process, Table 1 compared the performance of five algorithms commonly used in skin cancer identification. Each algorithm is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. According to these results, the Random Forest method provides the best performance with an accuracy of 85.33% and an F1-score of 0.8522, followed by K-Nearest Neighbor (KNN) with an accuracy of 82.5% and an F1-score of 0.8249. Thus, even though the resulting performance was adequate before the segmentation process, there was a significant increase in performance after the segmentation process using the proposed method was carried out. Table 2 displays the performance results of several algorithms used to identify skin cancer using the machine learning method, following the segmentation process using the hybrid clustering method.

Table 2. Skin Cancer Identification Using Machine Learning Methods with Segmentation

Methods	Performance Methods			
	Accuracy	Precision	Recall	F1-Score
Decision Tree (DT)	0.8366	0.8462	0.8366	0.8355
K-Nearest Neighbor (KNN)	0.8600	0.8627	0.8600	0.8597
Random Forest (RF)	0.8900	0.9011	0.8900	0.8892
Logistic Regression (LR)	0.8183	0.8350	0.8183	0.8160
Naïve Bayes (NB)	0.7783	0.7948	0.7783	0.7751

Table 2 previously compared the performance of five commonly used algorithms for skin cancer identification after the segmentation process. Each algorithm is evaluated using different performance metrics such as accuracy, precision, recall, and F1-score. According to these results, the Random Forest method provides the best performance with an accuracy of 89% and an F1-score of 0.8892, followed by K-Nearest Neighbor (KNN) with an accuracy of 86% and an F1-score of 0.8597. Thus, the RF method can be considered the most effective algorithm in this case. The hybrid clustering method in skin image segmentation resulted in an increase in accuracy and precision in separating suspicious areas from normal skin. This enables a clearer and more precise visual representation of the cancer area. Machine learning models trained using image data derived from hybrid clustering segmentation are able to recognize patterns that indicate the presence of skin cancer with a higher level of accuracy. The evaluation results show that the model is able to classify types of skin cancer with a satisfactory success rate.

This research makes an important contribution to the development of efficient and reliable diagnostic tools for the early detection of skin cancer. It is hoped that combining improved image segmentation technology and machine learning models can help health professionals in the early diagnosis and further treatment of patients with skin cancer. However, this study also has several limitations, including dependence on the quality of image data and the need for further validation of the proposed method. As a result, future research can focus on improving model performance, conducting experiments with larger datasets, and improving medical validation to test the method's reliability more thoroughly. In conclusion, this research provides a strong foundation for developing early skin cancer detection technology using machine learning and image segmentation approaches. It is hoped that the results of this research will provide great benefits in future efforts to prevent and treat skin cancer.

4. CONCLUSION

The test results utilizing the hybrid clustering segmentation method demonstrate a significant improvement in identifying skin cancer when compared to a scenario without the segmentation method. The proposed method for skin segmentation produces a more accurate and detailed representation of the skin image, enabling machine learning (ML) models to obtain more relevant and meaningful information in the skin cancer identification process. In tests using different performance metrics, like accuracy, precision, recall, and F1-score, the results of using ML to find skin cancer after the hybrid clustering segmentation process always show big improvements. Before hybrid clustering segmentation, the accuracy of identification results using the Random Forest method was 85.33%, but after segmentation, it increased to 89%. Similarly, precision, recall, and F1-score all increased significantly after implementing the hybrid clustering segmentation method. Thus, these results confirm that the proposed segmentation method effectively improves the ability of ML models to identify skin cancer diseases, providing more accurate and reliable results in clinical practice.

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