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Research Article

Comprehensive Analysis and Classification of Skin Diseases based on Image Texture Features using K-Nearest Neighbors Algorithm

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Abstract: Skin is the largest organ in humans, it functions as the outermost protector of the organs inside. Therefore, the skin is often attacked by various diseases, especially cancer. Skin cancer is divided into two, namely benign and malignant. Malignant has the potential to spread and increase the risk of death. Skin cancer detection traditionally involves time-consuming laboratory tests to determine malignancy or benignity. Therefore, there is a demand for computer-assisted diagnosis through image analysis to expedite disease identification and classification. This study proposes to use the K-nearest neighbor (KNN) classifier and Gray Level Co-occurrence Matrix (GLCM) to classify these two types of skin cancer. Apart from that, the average filter is also used for preprocessing. The analysis was carried out comprehensively by carrying out 480 experiments on the ISIC dataset. Dataset variations were also carried out using random sampling techniques to test on smaller datasets, where experiments were carried out on 3297, 1649, 825, and 210 images. Several KNN parameters, namely the number of neighbors (k)=1 and distance (d)=1 to 3 were tested at angles 0, 45, 90, and 135. Maximum accuracy results were 79.24%, 79.39%, 83.63%, and 100% for respectively 3297, 1649, 825, and 210. These findings show that the KNN method is more effective in working on smaller datasets, besides that the use of the average filter also has a significant contribution in increasing the accuracy.

Keywords: Comprehensive analysis of image recognition; Novel machine learning method; Image texture analysis; Skin disease detection; Skin disease recognition.

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1. Introduction

The skin is the largest organ of the human body, its mass is approximately 4 kg to 5 kg. The skin has a surface area of about 1.2 m^2 - 2.2 m^2. For this reason, the skin has many uses for humans, including protecting the body, adjusting body temperature, and being used for the sense of touch as well [1]. Therefore, skin disorders often occur due to several causative factors such as climatic conditions, place of residence, environment, unhealthy living habits, allergies, and so on. Skin cancer is a type of skin disease that needs special attention. This is because it is one of the three most dangerous and fastest-growing types of cancer [2]. Skin cancer generally affects Caucasian populations worldwide[3]. According to the Skin Cancer Foundation, the incidence of skin cancer globally continues to increase[4], this is also agreed with the World Health Organization (WHO) which states that one in every three cancer diagnoses is related to skin cancer[5]. The two types of skin cancer are benign or malignant[6]–[8]; both are caused by DNA damage due to exposure to ultraviolet radiation which causes uncontrolled cell proliferation[9]. Benign cancers such as seborrheic keratosis, cherry angioma, dermatofibroma, skin tags, pyogenic granulomas, and cysts[10]. Benign cancer generally does not spread even though it continues to grow. On the other hand, malignant cancer occurs in the patient's body, spreads uncontrollably, and can infiltrate other tissues or organs. [11], [12].

Skin cancer detection is usually done to determine whether skin cancer is malignant or benign, by carrying out a series of laboratory tests, but this method is considered too time-consuming [13], [14]. Therefore, computer-assisted diagnosis for the identification of skin diseases and classification through images is needed so that the process becomes fast. ML has been widely developed to help humans carry out various recognition tasks based on images and is currently also developing deep learning (DL) methods[15], [16]. Several machine learning (ML) classifiers that are widely used for skin disease classification are support vector machine (SVM), K-nearest neighbor (KNN), and Naïve Bayes (NB) [17], [18]. SVM has the advantage of being able to process non-linear data and handle high-dimensional data, but is sensitive to data scale so it requires appropriate pre-processing and is difficult to handle unbalanced data. NB has the advantage of simplicity and fast computing and does not require large amounts of data, but has the disadvantage of naive assumptions regarding feature independence and is sensitive to incomplete data. KNN has the advantage of being adaptive to changes in data, relatively simpler but is a lazy learner and sensitive to the number of neighbors (k). In the case of skin disease classification, these three methods have been compared in research [19], [20] and KNN is relatively superior, so in this research tests will be carried out on unbalanced data. Another reason why KNN is because it has no assumptions regarding data distribution, but needs to be selected on the right k.

Image features are an important input for training the classifier. In skin disease images, texture features are the most important thing. Texture can provide information about the pattern or consistency of the skin surface which can be useful for identifying certain skin diseases. Textural features may include smooth, rough texture, spots, or other characteristics of the skin surface[21]. One of the texture features that is popular and has high performance is the Gray Level Co-Occurrence Matrix (GLCM), this feature has been widely used in various classification studies such as skin diseases[22], [23], breast cancer[24], plant root[25], fruit quality [26], and fruit quality[27]. This proves that GLCM's performance is proven to be reliable for classification tasks. From several related studies on the classification of skin cancer, it is stated that the diagnosis of skin cancer can use computer assistance based on an image of the disease. Therefore, in this study, image classification will be carried out to help humans distinguish between benign and malignant skin diseases using the Gray Level Co-occurrence Matrix (GLCM) feature extraction method and the K-Nearest Neighbor (KNN) classification algorithm. The remainder of this paper is presented into four sections, namely related work in section two which explains motivating related research. Section three explains the proposed method along with detailed stages, section four contains implementation, results, and analysis. Section five is ablation studies, in this stage, we also get some findings about GLCM features and preprocessing impact. Finally closes with a conclusion section that explains conclusions, suggestions, and future work.

2. Related Work

There has been a lot of research related to classification or recognition, especially regarding skin diseases, some of which are [19], [20], [28], [29]. Pal [19], compared two ML methods, namely Random Forest (RF) and KNN. Based on the test results, it was found that the KNN method was superior to RF. KNN has an accuracy of 95.23%, which is approximately 1% superior to RF. Meanwhile, KNN's F1-score value is 0.04% superior to RF, namely 95.94%.

Nosseir and Shawky [20], also used KNN in their research, but this time KNN was compared with an SVM classifier. The texture feature used is a combination of first-order statistical and second-order statistical (GLCM). The difference between the first and second orders is that the first order does not consider the spatial relationship between the pixels. In this research, only small data was used, namely 240 images with 75% training data and 25% testing data. In the research, KNN was also superior, its accuracy reached 98.2%, while SVM was only 90%.

Hatem [28], also proposed a KNN classifier, but in his research, several stages of pre-processing and segmentation were carried out before feature extraction and classification. Several calculations such as asymmetry and compactness index, color, mean diameter, standard deviation, and PSNR are also taken into account. This research uses the dataset [30], and the results obtained are 98% accurate.

Another skin disease research conducted by Putri et.al [29] proposed an NB classifier with Local Binary Pattern (LBP) features. The uniqueness of this research is that it tested the

NB method in four experiments, with a different number of images chosen randomly from the ISIC dataset. These four experiments used small datasets, namely 225, 180, 135, and 90 for nine disease classes, namely Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus Pigmentosus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, Vascular Lesions. What is quite surprising is that the highest accuracy was obtained in the classification of 90 images with an accuracy of 94.44%, respectively, the other accuracies were 85.18%, 91.67%, and 82.2% for 135, 180, and 225 images respectively.

3. Proposed Method

Based on the literature described in the previous section, this research proposes to further study and test the KNN classifier and GLCM feature extraction for skin disease classification. In this research, an average filter was also used to carry out denoising before the features were extracted. Apart from that, this research also tested the performance of the KNN classifier on the full dataset and partial datasets using random sampling techniques. Briefly, Figure 1 illustrates the proposed method.

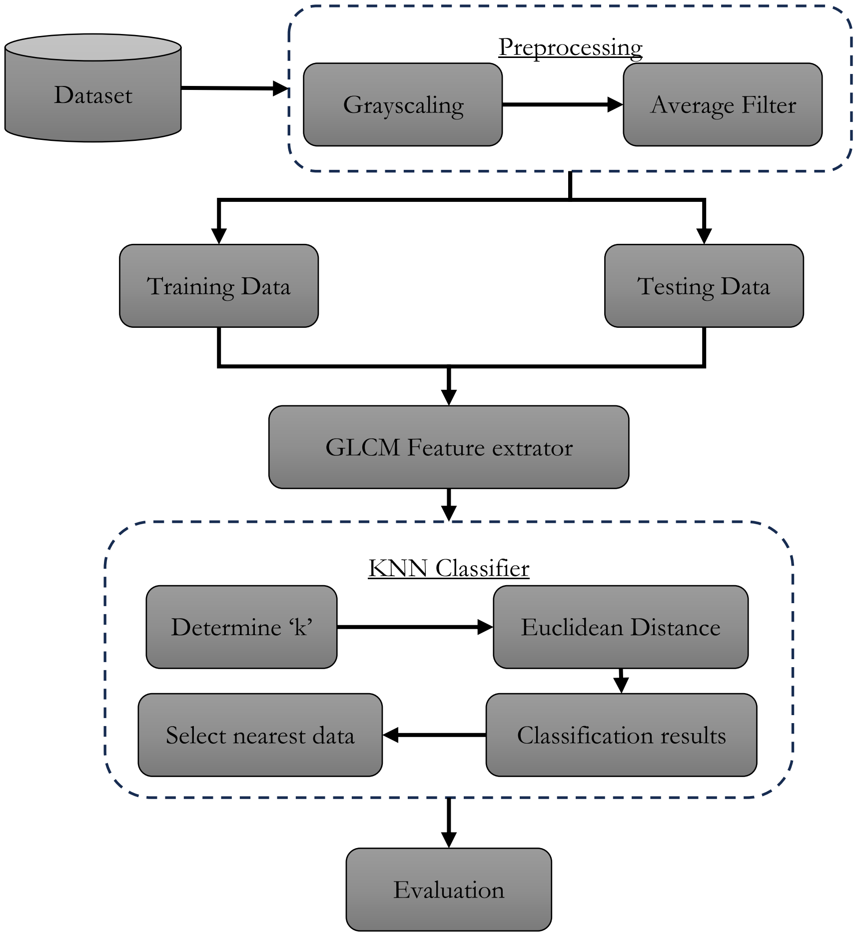


Figure 1. Proposed Method.

3.1. Dataset

The data collection process in this study uses a public dataset from https://www.kaggle.com/fanconic/skin-cancer-malignant-vs-benign. The data consists of 3297 disease images from malignant and benign tumor types, which were formed by The International Skin Imaging Collaboration (ISIC). The disease image data to be used consists of 2 data, namely benign and malignant image data. The total image data contained in the dataset is 3297 images. The pixel size of each image in the dataset is uniform, namely 224 x 224 pixels, so there is no need to crop or resize the pixel size to make it smaller. Figure 2 below shows a graph of the number of images contained in the dataset.

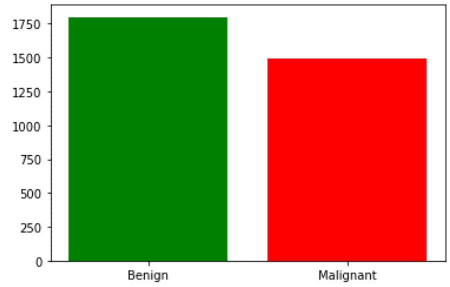


Figure 2. Graph of Image Class.

3.2 Preprocessing

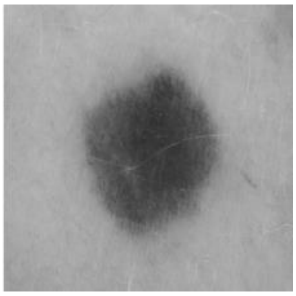
Image processing is carried out before the classification process using the K - nearest Neighbor algorithm. Below are some of the processes used in the image processing process:

3.2.1 Grayscaling Image

GLCM can only be extracted on grayscale images, not color images. Therefore, the first step is to convert the RGB image to a grayscale image. This can be done simply by taking the average of the components R (red), G (green), and B (blue), but to get more precise results, use Eq. (1) to get a grayscale image. A sample of the RGB to grayscale image conversion results is presented in Figure 3.

$$gray = (0.299 * R + 0.587 * G + 0.114 * B) \tag{1}$$

(a)

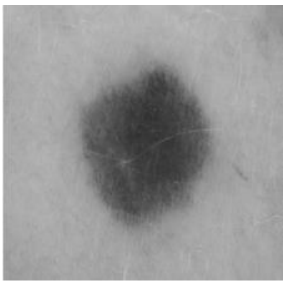


(b)

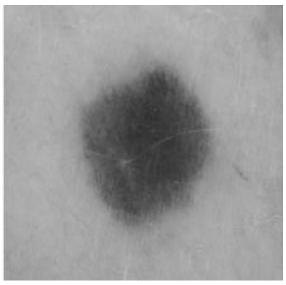
Figure 3. Conversion to RGB to Grayscale.

3.2.2 Average Filter

Images that have noise can reduce the quality of their features, therefore the noise needs to be minimized, namely by using an average filter. The average filter can reduce sharp changes or details in an image. This allows emphasis on larger structural information and reduces distractions from small details that may not be relevant. In some applications, such as object recognition, eliminating small, irrelevant details can improve the performance of feature extraction algorithms by focusing on the main characteristics of the object. In this study, an average filter (3.3) was used, which is not too large so that it does not cause an excessive blur effect. Fig. 4 presents an example of the results of the implemented average filter.



(a)



(b)

Figure 4. Denoising Image using Average Image.

3.3 Feature Extraction

The result of the image processing process is to support better feature extraction values. The application of the feature extraction method is obtained by using the Gray Level Co-Occurrence Matrix (GLCM) using angles of 0, 45, 90, and 135 in images of various types of tumor disease so that later it produces values of contrast, correlations, dissimilarity, energy, and homogeneity. Contrast measures the difference in intensity between pairs of pixels in an image. The greater the contrast value, the sharper the difference between the intensities of adjacent pixels in the image. It reflects how clear the borders are between objects in the image. Homogeneity measures the degree to which the intensity of pixels in an image approaches a uniform value. The higher the homogeneity value, the closer the pixel intensity in the image is to one average value. It reflects the degree of color consistency or intensity in the image. Energy measures the strength of texture patterns in an image. The greater the energy value, the stronger the texture pattern in the image. The maximum energy value is 1, which indicates a very strong and homogeneous texture. Correlation measures the degree to which pixel intensities in an image are linearly correlated. A higher correlation value indicates a linear relationship between pixel intensities in the image. Dissimilarity measures the degree to which pairs of pixels in an image are different from each other. The greater the dissimilarity value, the greater the difference between the intensities of adjacent pixels in the image. After obtaining this value, the classification process is carried out. The following are equations (2) to (6) in finding each feature in GLCM.

$$Contrast = \sum_i \sum_j (i-j)^2 \, p_{(i,j)} \tag{2}$$

$$Correlation = \sum_i \sum_j \frac{(i-\mu i)(j-\mu j)p_{(i,j)}}{\sigma i \sigma j} \tag{3}$$

$$Energy = \sum_i \sum_j p(i,j)^2 \tag{4}$$

$$Homogeineity = \sum_i \sum_j \frac{p(i,j)}{1+|i-j|} \tag{5}$$

$$Dissimilarity = \sum_i \sum_j p|i-j| \, \mathrm{p}(i-j)^2 \tag{6}$$

Where i and j: pixel intensity values in the image; $p_{(i,j)}$: the probability of appearance of intensity pair (i,j) in the image; μi and μj: average pixel intensities for i and j in the image; and σi and σj: standard deviation of pixel intensity for i and j in the image.

3.4 Classification

After feature extraction is carried out by generating the value of each feature from GLCM, the next step is classification by the K-Nearest Neighbor (KNN) algorithm. Then divide it into various classes and which data will be grouped, the system will classify the new data into the appropriate groups and determine the level of accuracy of the model.

KNN calculation starts from determining k, k is the closest number of power. For example using parameters with odd values, namely k=1, k=3, k=5, and so on. Next, calculate the distance between the testing image and the training image. By using the Euclidean distance as in equation (7), it can be used in calculating the distance between testing images. Then sort the results of the shortest distance search, place the closest neighbor according to the k that has been determined, then check the labels on the k closest data. Finally the testing images into majority classes according to the k closest neighbors based on training image data to determine whether the image is labeled as benign or malignant.

$$d(i,j) = \sqrt{|x_{i1}-x_{j1}|^2 + |x_{i2}-x_{j2}|^2 + \cdots + |x_{ip}-x_{jp}|^2} \tag{7}$$

Where i and j: indices are used to identify two images to be compared; $x_{i1}, x_{i2}, x_{i3}, \dots, x_{ip}$: variables or features in the ith data or object. There are p features to be compared; $x_{j1}, x_{j2}, x_{j3}, \dots, x_{jp}$variables or features in the jth data or object. This feature is the same as the i feature for the comparison being carried out.

4. Implementation and Results

In this section, the KNN method combined with GLCM and average filter is implemented on the ISIC dataset which has 3297 total images, consisting of 2637 training images and 660 testing images. Inspired by Putri et.al's research [29] which tested various types of dataset sizes, this research also tested using a random sampling method to form a smaller dataset. In total, there were four types of experiments in this study, which are presented in Table 1.

Table 1. Dataset distribution for Research Testing.

Test Number	Total Dataset	Training	Testing
1st	3297	2637	660
2nd	1649	1319	330
3rd	825	660	165
4th	210	200	10

In accordance with the stages of the proposed method, the image is converted to grayscale then an average filter is added, then features are extracted using GLCM feature extraction to obtain contrast, homogeneity, correlation, dissimilarity, and energy features at 4 angles, namely 0˚, 45˚, 90˚, and 135˚. Sample results from GLCM feature extraction are presented in Table 2. The results of these features are then used for the training process. By using KNN, after obtaining a model from the results of the training process, testing is carried out with existing test data based on the closest distance to all images in the training data using the Euclidean distance calculation method. After that, the results are evaluated using a confusion matrix to produce accuracy. In this research, testing was carried out with several k values in KNN, namely 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10, we also tested with different Euclidean distances, namely 1, 2, and 3. So there are 120 tests on each dataset size. Table 3 presents the recap results of the best KNN classifier values with different parameters.

Table 2. Sample of Extraction feature GLCM.

Sample image	GLCM feature	Degree			
		0˚	45˚	90˚	135˚
Benign _1	Contrast	9.5065	10.4352	6.7401	15.0979
	Homogeneity	0.3911	0.3931	0.4373	0.3371
	Energy	0.0544	0.0547	0.0589	0.0502
	Correlation	0.9967	0.9964	0.9977	0.9948
	Dissimilarity	2.1544	2.2	1.812	2.714
Benign _2	Contrast	12.8018	16.8154	8.9041	17.3673
	Homogeneity	0.33	0.2997	0.3856	0.298
	Energy	0.0514	0.049	0.0572	0.0489
	Correlation	0.9948	0.9932	0.9964	0.993
	Dissimilarity	2.6141	2.9745	2.1188	3.0062
Benign_3	Contrast	29.7803	31.755	21.6566	44.1456
	Homogeneity	0.2386	0.2367	0.2691	0.2047
	Energy	0.0247	0.0246	0.0263	0.0229
	Correlation	0.9952	0.9948	0.9965	0.9928
	Dissimilarity	4.0148	4.108	3.4228	4.8835
Malignant_1	Contrast	42.4196	86.5284	55.4139	80.7552
	Homogeneity	0.3149	0.288	0.3625	0.267
	Energy	0.0346	0.0327	0.0381	0.0311
	Correlation	0.9898	0.9793	0.9867	0.9806
	Dissimilarity	4.0208	4.8946	3.5286	5.119
Malignant_2	Contrast	97.7438	111.25	59.9091	143.274
	Homogeneity	0.2308	0.1915	0.2632	0.1927

	Energy	0.0203	0.018	0.0218	0.0181
	Correlation	0.9833	0.981	0.9898	0.9755
	Dissimilarity	5.9124	6.9068	4.7721	7.2525
Malignant_3	Contrast	105.4028	163.3285	101.3207	164.7551
	Homogeneity	0.2545	0.2119	0.2695	0.2194
	Energy	0.0236	0.0206	0.0238	0.0213
	Correlation	0.9818	0.9717	0.9825	0.9714
	Dissimilarity	6.0564	7.5805	5.7764	7.5473

Table 3. Accuracy results from various parameters (k, d, and degrees).

Total Dataset	Accuracy			Max acc parameter
	Average	Max	Min	
3297	0.7593	0.7924	0.7000	k=5, d=2, degree=90
1350	0.7583	0.7939	0.6909	k=9, d=3, degree=0, and k=7, d=3, degree=0
825	0.7955	0.8485	0.7272	k=10, d=1, degree=0
210	0.9575	1.0000	0.8000	80/120 testing has maximum accuracy results

We have carried out a total of 480 experiments, of which 120 were tested for each dataset. The selection of datasets on smaller data sets was done by random sampling. Based on the results presented in Table 3, it appears that the maximum accuracy on the smallest dataset reaches 1, this is a perfect classification result. However other findings are different from theory, where the more data, the better the learning and classification process should be. But in this case, the results are the opposite, accuracy on small datasets is much better. This result is in line with research[29], this is because KNN tends to be able to avoid overfitting, small datasets are more representative of various cases, distance calculations are more efficient, and their model is simple. On large datasets, the risk of overfitting increases, and distance calculations can be more complicated, while more complex models may be needed to understand greater variations in the data[31].

5. Ablation Studies

In this research, we also conducted several ablation studies to prove the effectiveness of the proposed method. It is no secret that GLCM is a popular feature extraction, in research [32], the number of GLCM features was analyzed for its effect on batik image classification, but the results using four and five features produced identical accuracy. Because the GLCM feature used in this study uses a relatively unpopular dissimilarity feature, but based on the experimental results presented in Tables 4 to 7, it is proven that in this case the dissimilarity feature and average filter have an important role in increasing the accuracy results.

Table 4. Results of the ablation study on 3297 images show an average accuracy.

GLCM degree	4 features GLCM		5 features GLCM	
	with average filter	without average filter	with average filter	without average filter
0	0.7567	0.7233	0.7557	0.7246
45	0.7575	0.7123	0.7609	0.7250
90	0.7586	0.7135	**0.7645**	0.7169
135	<u>0.7611</u>	0.7199	0.7595	0.7240

Table 5. Results of the ablation study on 1350 images show an average accuracy.

GLCM degree	4 features GLCM		5 features GLCM	
	with average filter	without average filter	with average filter	without average filter
0	<u>0.7699</u>	0.7200	**0.7705**	0.7265
45	0.7650	0.7259	0.7594	0.7384
90	0.7438	0.6925	0.7438	0.6958
135	0.7640	0.7218	0.7594	0.7093

Table 6. Results of the ablation study on 825 images show an average accuracy.

GLCM degree	4 features GLCM		5 features GLCM	
	with average filter	without average filter	with average filter	without average filter
0	0.7949	0.7568	0.7949	0.7705
45	**0.8044**	0.7615	**0.8044**	0.7735
90	0.7833	0.7461	0.7833	0.7608
135	<u>0.7993</u>	0.7396	<u>0.7993</u>	0.7503

Table 7. Results of the ablation study on 210 images show an average accuracy.

GLCM degree	4 features GLCM		5 features GLCM	
	with average filter	without average filter	with average filter	without average filter
0	0.9500	0.8467	0.9467	0.9033
45	0.9600	0.8600	**0.9667**	0.8767
90	<u>0.9633</u>	0.8833	0.9567	0.8967
135	0.9567	0.8400	0.9400	0.8633

Based on the results presented in Tables 4 to 7, there appears to be a slight increase in performance when using five features (contrast, homogeneity, correlation, energy, and dissimilarity) compared to four features (without dissimilarity), this related to how these features complementarily describe textures in skin images that are associated with disease. The Dissimilarity feature measures the difference between pairs of pixel intensities in an image. In the context of skin disease classification, greater differences between the textures that characterize benign and malignant diseased skin could be important information for the model. The Dissimilarity feature describes these differences well. The average filter can help even out some of the small details in an image and reduce noise. This can help in maintaining consistency in texture representation across different skin images and assist the model in recognizing more general patterns rather than patterns that are very specific to one particular image. By smoothing the image, you may have improved the model's ability to extract relevant GLCM features and classify skin more consistently.

6. Conclusions

This research has succeeded in comprehensively analyzing the classification of skin disease methods based on the KNN classifier and GLCM feature extraction. Based on the results of tests carried out on the complete ISIC dataset, it turns out that the resulting classification accuracy is only around 0.76. This is not a satisfactory result and the implementation of standard ML methods may not be interesting enough, but this research can provide findings and contribute to a deeper analysis of the implementation of KNN methods. Some surprising findings are the increased accuracy after applying the average filter, implementation on small datasets, and the role of dissimilarity features. KNN performance is influenced by quite a lot of parameters, such as k, d, and degree, where the results are quite varied. This confirms that the application of the KNN method must be done carefully to determine the parameters. Implementation on small datasets also turns out not to always give bad results, because KNN has better performance in this case. In the future, a comprehensive analysis of ML and DL needs to be carried out so that it can be used as a reference to determine the most suitable implementation method for a classification case, especially in skin disease.

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