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Article

Classification of Skin Cancer Diseases Using KNN, CNN and SVM Methods

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Abstract. According to the WHO, about 2 to 3 million non-melanoma.non-melanoma skin cancers and 132,000 melanoma skin cancers occur globally every year, making up one out of every three cancers.globally each year, and account for one in every three cancers diagnosed.diagnosed. In Indonesia, skin cancer is listed as the cancer with the third highestincidence after uterine cervical and ovarian cancer, and breast cancer.Skin cancer can be detected with dermoscopy. Dermoscopy is a non-invasive diagnostic technique using optical magnification that allows visualization of morphologicHowever, this cannot be done optimally because it still relies on manual analysis so it cannot classify skin cancer types on larger datasets with potential errors and low accuracy. To accurately determine the type of skin cancer,a better classification method is needed. The purpose of this research is to determine the accuracy of skin cancer calcification using Convolutional Neural Network (CNN), support vector machine (SVM), K-nearest neighbor (KNN) models. The datasheet used amounted to 2,239 containing skin cancer images with class division 114 actinic keratosis, 376 basal cell carcinoma, 95 dermatofibroma, 438 melanoma, 357 nevus, 462 pigmented benign, 77 seborrheic keratosis, 181 squamos cell, 139 vascular lesion. The results showed that the convolutional neural network (CNN) algorithm model obtained a sensitivity of 92.59%, specificity of 99%, precision of 93%, F1-Score of 93.01%, and accuracy of 98.35%. For the KNN algorithm model, 57.77% sensitivity, 94.53% specificity, 64.25% precision, 55.99% F1-Score, and 90.45% accuracy were obtained. And for the SVM algorithm model, 61% sensitivity, 94.81% specificity, 70.23% precision, 61.26% F1-Score, and 91.17% accuracy were obtained.

Keywords: Skin cancer, Dermoscopy, Convolutional Neural Network (CNN), support vector machine (SVM), K-nearest neighbor (KNN), Accuracy

1. Introduction

The skin is a part of the human body that is directly exposed to the sun because the skin is the outermost layer of the body. Excessive sun exposure and exposure to ultraviolet radiation are certainly harmful to the skin because they can cause skin cancer. GLOBOCAN 2020 statistical data from the World Health Organization states that the total number of deaths due to cancer in the world reaches 9.9 million people. This figure shows that cancer is one of the leading causes of death in the world. An excessive lump or growth of skin tissue that affects part or all of the skin layer is called skin cancer. The structure of this skin cancer is irregular, with cell differentiation in the chromatin, nucleus, and cytoplasm at various levels. Skin cancer grows and absorbs quickly, damaging surrounding tissue and metastasing through blood vessels and/or lymph vessels. Using a biopsy, dermatologists usually diagnose skin cancer by taking a small sample of skin tissue and then examining it in a laboratory. Biopsies are very expensive and can injure or scratch human skin. Different types of skin cancers include Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign, Seborheic Keratosis, Squamos Cell, Vascular Lesion.

About more than one million cases of skin cancer occurred in 2018 globally. Skin cancer is one of the fastest growing diseases in the world. In addition, the number of cancer patients is increasing due to smoking behavior, environmental changes, and the influence of other factors such as radiation, viruses and alcohol. The most common and dangerous type of cancer is skin cancer. Skin cancer can be in the form of unusual swelling of skin cells. Skin cancer spreads all over the world and is a dangerous disease.

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According to the WHO, the number of melanoma cases diagnosed each year has increased by 53%, and the mortality rate will continue to rise. Early misdiagnosis leads to a cure rate and survival index of less than 14%. However, if skin cancer detection can be done early, then the survival rate can increase by about 97%. Reports of skin cancer problems continue to grow with the most common types of cancer being non-melanocytes such as basal cell carcinoma and squamous cell carcinoma. Meanwhile, non-melanocytic skin cancers are the basic forms that can be found, such as basal cell carcinoma and squamous cell carcinoma. To increase the cure rate, early diagnosis is the main thing because if this cancer is detected for a long time then the disease has penetrated far enough into the skin then it can be difficult to cure and cause death. Early diagnosis of skin cancer is helpful for cancer treatment, although it is still possible that the condition cannot be cured when the disease has progressed beyond the skin.

The diagnosis of malignant melanoma in patients is essential to prevent the cancer from metastasizing to other organs because research shows that early detection and treatment increase the patient's chances of recovery. There are many methods and approaches to detecting cancer. However, with the development of the current times, the old approaches have been abandoned and new methods such as machine learning, deep learning, transfer learning, and other methods are used. Detection and classification methods are also diverse. By using deep learning on image processing, artificial intelligence (AI)-based solutions can help medical workers screen and classify cancer types. The ability of this model to recognize patterns by using its image features accurately allows this AI solution to do so. In addition, because this model has high accuracy, the chances of skin cancer in patients can be detected quickly. With the development of AI technology in this day and age to make it easier in everything. For this reason, the author develops a website that has accurate results and reliable solutions, the author develops a website application that utilizes the KNN, CNN and SVM algorithms as a method of classification of skin cancer diseases to assist doctors in diagnosing skin diseases. Therefore, a final project was made with the title "Classification of Skin Cancer Diseases Using KNN, CNN and SVM Methods"

2. Theoretical Studies

Previous research was conducted by Muhammad Faruk and Nur Nafi'iyah (2020) who have compiled a journal entitled "Classification of Skin Cancer Based on Texture Features, Image Color Features Using SVM and KNN", this research was conducted to assist dermatology teams in early detection of skin cancer. The features used are grayscale imagery, the features of average values, standard deviation, skewness, entropy, variance, contrast, energy, correlation, and homogeneity. Furthermore, the value of the feature is trained and classified. The results of the classification using the SVM algorithm, the accuracy value is 69.85%, and the accuracy using the KNN algorithm, with the value of K=2 the accuracy is 67.27%, K=3 the accuracy is 67.88%, K=4 the accuracy is 70.15%, K=5 the accuracy is 70.61%, K=6 the accuracy is 69.55%. Thus, the best K in KNN is 5, with an accuracy of 70.61%, where the data used are 2637 images as training datasets, 660 images as test data and classified into malignant skin cancer classes, and benign skin cancer.

The next research was conducted by Youllia Indrawaty Nurhasanah, Irma Amelia Dewi, Fevly Pallar (2020) who have compiled a journal entitled "Melanoma Cancer Type Recognition System in Images Using Gray Level Cooccurrence Matrices (GLCM) and K-Nearest Neighbor (KNN) Classifier" which in this study has created a system that can help medical parties predict a type or type of melanoma cancer with processes including, optimization of postprocessing through morphological closing, the formation of gray level co-occurrence matrices (GLCM) for the extraction of statistical texture features and K-Nearest Neighbor (KNN) as the classification method. The results of the test showed that the extraction of statistical texture characteristics was useful in the recognition of this cancer where the accuracy was obtained reaching 93.33% by classifiers in the melanoma positive testing category and 86.66% in the melanoma class category

The third research is a research conducted by A. Bukhori Muslim (2022) who has compiled a journal entitled "Skin Cancer Detection System Using Statistical Texture and K-Nearest Neighbor (K-NN) Feature Extraction Method". In the image classification study using the K-Nearest Neighbor (K-NN) classification method, it produced a skin cancer detection system with the best accuracy of 80% when tested using a combination of 4 GLCM features (Contrast, Correlation, Energy and Homogeneity).

Next is research conducted by Rizky Adawiyah, Dadang Iskandar Mulyana (2022) with the title "Optimization of Skin Disease Detection Using the Support Vector Machine (SVM) and Gray Level Co-occurrence Matrix (GLCM) Methods". The results of the study show that this skin disease detection system can display the results of the type of skin disease and based on the test results of several data samples that the best accuracy value is 90% of the results of this skin disease detection classification.

The next research is a research conducted by Findriyani, Rizal Adi Saputra (2024) with the title "Classification of Skin Cancer Based on Benign and Malignant Image Data Using Convolutional Neural Network", The results of this study show that in the 50th epoch, the model achieved an accuracy level of 99.01%. This success signifies CNN's ability to distinguish between benign and malignant skin cancers with a high degree of accuracy. The implications can be used to support rapid diagnosis and more effective treatment in skin cancer patients, helping to improve the quality of treatment and providing significant benefits in the medical field.

Based on the results of previous research using various approaches and designs to classify skin cancers fairly accurately. However, research on the classification of skin cancer types is still limited, especially in the classification of skin cancers with the categories of Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign, Seborheic Keratosis, Squamos Cell, Vascular Lesion. Therefore, further research is needed that can classify the types of skin cancer of patients with different systems and amounts of datasets. Therefore, in this study, the author made "Skin Cancer Disease Classification System Using the K-Nearest Neighbor (K-NN) Method, convolutional neural network (CNN), Support vector machine (SVM)"

3. Research Method

This research went through several stages which included skin cancer data collection, model planning, testing programs, and disease classification in the CNN, SVM and K-NN methods. The stages of the research are described in figure 1 below.

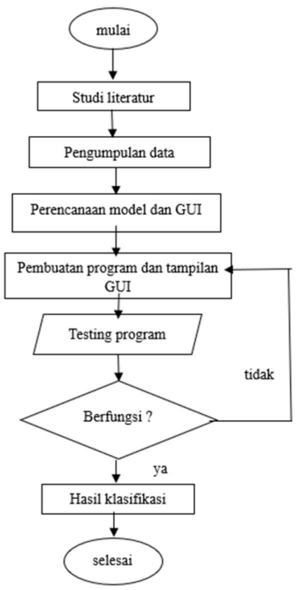


Figure 1. Stages of research

Source : Primary Data Processing 2023

In this study, it is necessary to collect dermoscopy image datasheets of skin cancer diseases. Data collection for this study used access to the Kaggle website with the source https://www.kaggle.com/datasets/nodoubttome/skin-cancer9- classesisic with JPG format totaling 2,239 containing skin cancer images used as training data with class division 114 actinic keratosis, 376 basal cell carcinoma, 95 dermatofibroma, 438 melanoma, 357 nevus, 462 pigmented benign, 77 seborheic keratosis, 181 squamos cell, 139 vascular lesion.

Processing of skin cancer disease through the stages of image resize, image segmentation, and image classification using CNN, SVM and K-NN methods. These stages can be seen in figure 2.

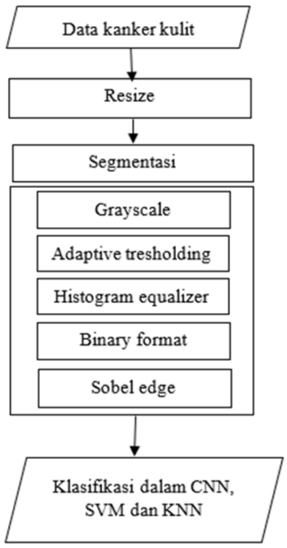


Figure 2. Image Processing

This image processing stage includes the process of (1) image resize, which is standardizing the overall image size to a size of 256 × 256 pixels. (2) image segmentation process. In this process, the image will be processed into grayscale. Where this image shows a degree of grayness, with black having low intensity while white having high intensity. The adaptive tresholding method is the process of producing an image that has two values at the gray level, black and white, which is called binary. Histogram equalizer method, which is a method that usually increases the contrast and sharpness of the image. The binary format method or binary image is an image process consisting of pixels colored one of two colors, usually black and white. This image stores each pixel in a single bit, i.e. 0 or 1. Next, enter the image processing process using the sobel edge detection method. An edge detector functions to identify the edges of an image object.

After the image segmentation process is carried out, the image image will be classified by applying the K-NN (K- Nearest Neighbor), CNN (Convolutional Neural Network), and SVM algorithms

(Support Vector Machine). The KNN algorithm is a method used to classify data based on the shortest distance to the data object. The determination of the best K-value for this algorithm is based on the available data. A high K-value can reduce the effect of noise on classifications, it can also make the boundaries between each classification more blurred. Convolutional Neural Network (CNN) is a deep learning algorithm used to process image data inputs, determine importance (weight and biases that can be learned) to various aspects in the image and function to distinguish one object from another. Support Vector Machine or SVM is a method in supervised learning classification and Support Vector Regression. SVM can solve classification and regression problems with linear and non-linear.

4. Results and Discussion

This study classified nine image classes, namely Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign, Seborheic Keratosis, Squamos Cell, Vascular Lesion using Convolutional Neural Network (CNN), Support vector machine (SVM), K- Nearest Neighbor (KNN) methods. The dataset used comes from a secondary source, namely the Kaggle website. The programming language used is Python. The main process in data processing is at the segmentation stage.

4.1 **Data collection**

The dataset was downloaded from https://www.kaggle.com/datasets/nodoubttome/skin-cancer9- classesisic in JPG format totaling 2,239 containing skin cancer images used as training data with class division 114 actinic keratosis, 376 basal cell carcinoma, 95 dermatofibromas, 438 melanomas, 357 nevus, 462 pigmented Benign, 77 seborheic keratosis, 181 squamos cells, 139 vascular lesions, with the distribution of test data for each class is 15 test images, the number of datasheets is shown in Table 1.

Table 1. Datasheet

Datasheet	Sum
actinic keratosis	114
Basal Cell Carcinoma	376
Dermatofibroma	95
Melanoma	438
Nevus	357
pigmented benign	462
Seborheic keratosis	77
Squamos Cell	181
vascular lesion	139
Total Image	**2.239**

Source : Primary Data Processing 2023

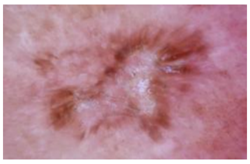
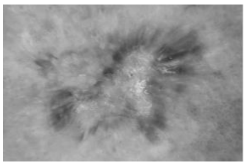
4.2 **Resize Image**

In this study, all image sizes were thoroughly set to 256 × 256 pixels. The purpose of this resize is to ensure consistency and uniformity in the data to be used, support computational efficiency 55, and meet model requirements.

4.3 **Grayscale**

Before starting the segmentation and extraction process, the image data needs to be converted into a grayscale image. This makes it possible to simplify the image model. Grayscale or grayish imagery has only one value that presents red, green, and blue values. The degree of gray imagery has 8 bits of binary value or a scale of 0-255, where the value 0 is black and 255 is white. Some of the results can be seen in Table 4.2.

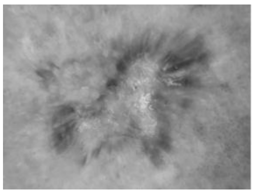
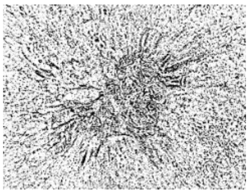
Table 2. Grayscale Process

Original image	**Greyscale imagery results**
	

4.4 **Image segmentation**

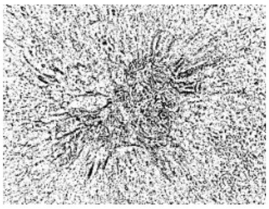
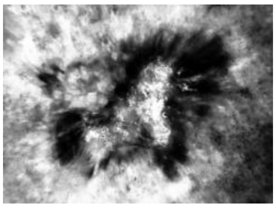
In the segmentation process, the image will be processed through 4 processes, namely the Adaptive tresholding process, Histogram Equalition, Binary format, and sobel edge. Adaptive tresholding is a process to produce an image that has two values at the gray level, black and white, which is called binary. The adaptive treshold image processing process can be seen in table 4.3 below:

Table 3. Adaptive Tresholding Process

Grayscale	**Adaptive tresholding *imagery results***
	

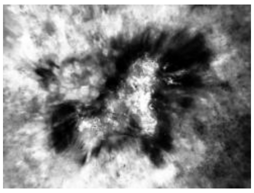
After going through the adaptive tresholding process, the image will also be processed through the equalizer histogram method, which is a method that usually increases the contrast of the image. The process of equalizer histogram image processing can be seen in table 4.4 below:

Table 4. Process of Histogram Equalizer

Adaptive Tresholding	**Histogram Equalizer *Image Results***
	

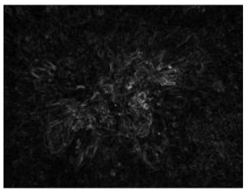
After the equalizer histogram process, the image will be processed on the binary format method or binary imagery which is an image process consisting of pixels colored in one of two colors, usually black and white. This image stores each pixel in a single bit, i.e. 0 or 1. The process of processing this binary image can be seen in table 4.5 below:

Table 5. Binary Format Process

Histogram equalizer	**Binary format *image results***
	

Next, enter the image processing process using the sobel edge detection method. An edge detector functions to identify the edges of an image object. Some of the results of the image segmentation process using the sobbel edge detection method can be seen in table 4.6 below:

Table 6. Sobel Edge Detection Process

Binary format	**Sobel edge imagery**
	

4.5 **Evaluation of Metrics**

Confusion matrix is a matrix that provides information comparing the classification results carried out by the system with the actual classification results. The performance of the convolutional neural network (CNN) algorithm is obtained from the confusion matrix. The confusion matrix table is used to get the evaluation of metrics such as accuracy, recall, precision, F1-Score.

$$\text{Accuracy} = (1)\ \frac{\boldsymbol{True\ Positive+True\ Negative}}{\boldsymbol{Jumlah\ Data}}$$

$$\text{Precision} = (2)\frac{\boldsymbol{True\ Positive}}{\boldsymbol{True\ Positive+False\ Positive}}$$

$$\text{Sensitivity} = (3)\frac{\boldsymbol{True\ Positive}}{\boldsymbol{True\ Positive+False\ Negative}}$$

$$\text{Specificity} = (4)\frac{\boldsymbol{True\ Negative}}{\boldsymbol{True\ Negative+False\ Positive}}$$

$$\text{F1 Score} = 2\times\ (5)\ \frac{\boldsymbol{presisi\times recall}}{\boldsymbol{presisi+recall}}$$

The results *of the confusion matrix* from the *convolutional neural network* (CNN) algorithm are shown in Figure 3. Confusion matrix cnn.

actual values \ predicted values	actinic keratosis	basal cell	dermatofibroma	melanoma	nevus	seborheic	pigmented benign	squamos	vascular lesion
actinic keratosis	13	0	0	0	2	0	0	0	0
basal cell	0	15	0	0	0	0	0	0	0
dermatofibroma	0	0	14	0	0	0	0	1	0
melanoma	0	0	0	15	0	0	0	0	0
nevus	0	0	0	0	15	0	0	0	0
seborheic keratosis	0	0	0	2	0	13	0	0	0
pigmented benign	0	1	0	1	0	0	13	0	0
squamos cell	0	2	0	0	0	0	0	13	0
vascular lesion	0	0	1	0	0	0	0	0	14

Figure 3. Confusion Matrix CNN

In this study, a confusion matrix was found as seen in Figure 3. Based on the results of the confusion matrix above, a score of 13 True Positive (TP) of the actinic keratosis class and 120 True Negative (TN) of the actinic keratosis class, 2 False Negative (FN) of the actinic keratosis class, 0 False Positive (FP) of the actinic keratosis class. 15 True Positive (TP) of the basal cell class and 117 True Negative (TN) of the basal cell class, 0 False Negative (FN) basal cell class, 3 False Positive (FP) basal cell class. 14 True Positive (TP) dermatofibroma class and 119 True Negative (TN) dermatofibroma class, 1 False Negative (FN) dermatofibroma class, 1 False Positive (FP) dermatofibroma class. 15 True Positive (TP) melanoma class and 117 True Negative (TN) class melanoma, 0 False Negative (FN) class melanoma, 3 False Positive (FP) class melanoma. 15 True Positive (TP) class nevus and 118 True Negative (TN) class nevus, 0 False Negative (FN) class nevus, 2 False Positive (FP) class nevus. 13 True Positive (TP) class seborheic keratosis and 120 True Negative (TN) class seborheic keratosis, 2 False Negative (FN) class seborheic keratosis, 0 False Positive (FP) class seborheic keratosis. 13 True Positive (TP) class pigmented benign and 120 True Negative (TN) class pigmrnted benign, 2 False Negative (FN) class pigmented benign, 0 False Positive (FP) class pigmented benign. 13 True Positive (TP) class squamos cell and 119 True Negative (TN) class squamos cells, 2 False Negative (FN) class squamos cells, 1 False Positive (FP) class squamos cell. 14 True Positive (TP) class vascular lesion and 120 True Negative (TN) class vascular lesion, 1 False Negative (FN) class vascular lesion, 0 False Positive (FP) vascular lesion class. Based on the values in the confusion matrix, accuracy, precision, sensitivity, specificity, and F1-Score are calculated using equations (1), (2), (3), (4), and (5).

actual values \ predicted values	actinic keratosis	basal cell	dermatofibroma	melanoma	nevus	seborheic	pigmented benign	squamos	vascular lesion
actinic keratosis	8	4	0	1	2	0	2	0	0
basal cell	1	13	1	0	0	0	0	0	0
dermatofibroma	0	1	6	3	0	0	4	0	1
melanoma	0	0	0	7	4	1	3	0	0
nevus	0	0	0	0	15	0	0	0	0
seborheic keratosis	0	3	0	10	1	1	0	0	0
pigmented benign	0	5	1	0	0	0	9	0	0
squamos cell	0	0	1	2	1	0	2	9	0
vascular lesion	0	4	0	0	0	0	1	0	10

Figure 4. Confusion Matrix KNN

In the study using the knn method, a confusion matrix was found as seen in Figure 4. Based on the results of the confusion matrix above, a score of 8 True Positive (TP) of the actinic keratosis class and 119 True Negative (TN) of the actinic keratosis class, 7 False Negative (FN) of the actinic keratosis class, and 1 False Positive (FP) of the actinic keratosis class. 13 True Positive (TP) basal cell class and 103 True Negative (TN) basal cell class, 2 False Negative (FN) basal cell class, 17 False Positive (FP) basal cell class. 6 True Positive (TP) dermatofibroma class and 117 True Negative (TN) dermatofibroma class, 9 False Negative (FN) dermatofibroma class, 3 False Positive (FP) dermatofibroma class. 7 True Positive (TP) melanoma class and 104 True Negative (TN) melanoma class, 8 False Negative (FN) melanoma class, 16 False Positive (FP) melanoma class. 15 True Positive (TP) nevus class and 112 True Negative (TN) nevus class, 0 False Negative (FN) nevus class, 8 False Positive (FP) nevus class. 1 True Positive (TP) of seborheic keratosis class and 119 True Negative (TN) of seborheic keratosis, 14 False Negative (FN) of seborheic keratosis, 1 False Positive (FP) of seborheic keratosis. 9 True Positive (TP) grade pigmented benign and 108 True Negative (TN) grade pigmented benign, 6 False Negative (FN) grade pigmented benign, 12 False Positive (FP) grade pigmented benign. 9 True Positive (TP) class squamos cell and 119 True Negative (TN) class squamos cell, 6 False Negative (FN) class squamos cell, 0 False Positive (FP) class squamos cell. 10 True Positive (TP) class vascular lesion and 119 True Negative (TN) class vascular lesion, 5 False Negative (FN) class vascular lesion, 1 False Positive (FP) class vascular lesion. Based on the values in the confusion matrix, accuracy, precision, sensitivity, specificity, and F1-Score are calculated using equations (1), (2), (3), (4), and (5).

	predicted values								
actual values	actinic keratosis	basal cell	dermatofibroma	melanoma	nevus	seborheic	pigmented benign	squamos	vascular lesion
actinic keratosis	8	4	0	1	2	0	2	0	0
basal cell	1	13	1	0	0	0	0	0	0
dermatofibroma	0	1	6	3	0	0	4	0	1
melanoma	0	0	0	7	4	1	3	0	0
nevus	0	0	0	0	15	0	0	0	0
seborheic keratosis	0	3	0	10	1	1	0	0	0
pigmented benign	0	5	1	0	0	0	9	0	0
squamos cell	0	0	1	2	1	0	2	9	0
vascular lesion	0	4	0	0	0	0	1	0	10

Figure 5. Confusion Matrix SVM

Using these equations, for the KNN algorithm model, sensitivity of 57.77%, specificity of 94.53%, precision of 64.25%, F1-Score of 55.99%, and accuracy of 90.45% were obtained.

In the study using the svm algorithm method, a confusion matrix was found as seen in Figure 5. Based on the results of the confusion matrix above, a value of 6 True Positive (TP) of the actinic keratosis class and 120 True Negative (TN) of the actinic keratosis class, 9 False Negative (FN) of the actinic keratosis class, 0 False Positive (FP) of the actinic keratosis class. 11 True Positive (TP) of the basal cell class and 114 True Negative (TN) of the basal cell class, 4 False Negative (FN) basal cell class, 6 False Positive (FP) basal cell class. 7 True Positive (TP) dermatofibroma class and 118 True Negative (TN) dermatofibroma class, 8 False Negative (FN) dermatofibroma class, 2 False Positive (FP) dermatofibroma class. 11 True Positive (TP) melanoma class and 102 True Negative (TN) class melanoma, 4 False Negative (FN) class melanoma, 18 False Positive (FP) class melanoma. 10 True Positive (TP) class nevus and 108 True Negative (TN) class nevus, 5 False Negative (FN) class nevus, 12 False Positive (FP) class nevus. 5 True Positive (TP) class seborheic keratosis and 120 True Negative (TN) class seborheic keratosis, 10 False Negative (FN) class seborheic keratosis, 10 False Positive (FP) class seborheic keratosis. 8 True Positive (TP) class pigmented benign and 114 True Negative (TN) class pigmented benign, 7 False Negative (FN) class pigmented benign, 6 False Positive (FP) class pigmented benign. 9 True Positive (TP) class squamos cell and 120 True Negative (TN) class squamos cell, 6 False Negative (FN) class squamos cell, 4 False Positive (FP) class squamos cell. 13 True Positive (TP) class vascular lesion and 113 True Negative (TN) class vascular lesion, 2 False Negative (FN) class vascular lesion, 7 False Positives (FP) vascular lesion class. Based on the values in the confusion matrix, accuracy, precision, sensitivity, specificity, and F1-Score are calculated using equations (1), (2), (3), (4), and (5).

Using these equations, for the SVM algorithm model, 61% recall, 94.81% specificity, 70.23% precision, 61.26% F1-Score, and 91.17% accuracy were obtained.

Next, the author will compare the value of the evaluation matrix of the 3 algorithm methods which will be shown in the image below.

Table 7. Algorithm Results Comparison

Yes	Type	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1 Score (%)
1	*CNN*	98,35%	93%	92,59%	99%	93,01%
2	*SVM*	91,17%	70,23%	61%	94,81%	61,26%
3	*KNN*	90,45%	64,25%	57,77%	94,53%	55,99%

rom Table 2, performance analysis was carried out by comparing the accuracy, precision, sensitivity, specificity, and value of the F1-Score algorithm model of the convolutional neural network (CNN), support vector machine (SVM), and K- nearest neighbor (KNN) algorithms. Based on the results of the calculations carried out, the highest accuracy value for the model is the convolutional neural network (CNN) to detect skin cancer. The accuracy value in the convolutional neural network (CNN) model is 98.35%, while in the support vector machine (SVM) model, an accuracy value of 91.17% is obtained, and the smallest accuracy obtained by using the model, namely K-nearest neighbor (KNN), is only 90.45%. So that after obtaining the classification results of each algorithm, to see more clearly, it can be seen with the ROC (Receiver Operating Characteristic) curve which can describe the performance of each method, namely CNN, KNN and SVM as seen in Figure 4.4.

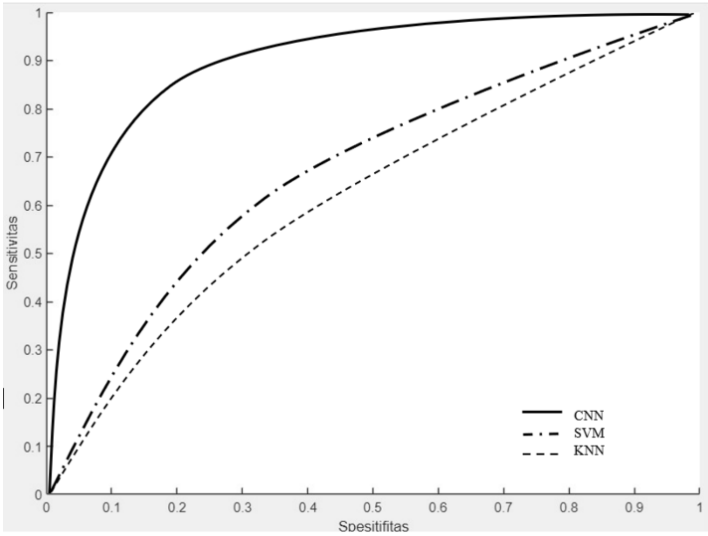


Figure 6. ROC Curve

From figure 6, performance analysis was carried out by comparing the accuracy, precision, sensitivity, specificity, and F1-Score algorithm values of convolutional neural network (CNN), support vector machine (SVM), and K- nearest neighbor (KNN) algorithms. Based on the results of the calculations carried out, the highest sensitivity value for the model is the convolutional neural network (CNN) to detect skin cancer. The sensitivity value in the convolutional neural network (CNN) model was 92.59%, while in the support vector machine (SVM) model, the sensitivity value was 61% and the smallest sensiiviats obtained were obtained using the model, namely K- nearest neighbor (KNN) only 57.77%. For AUC (Area Under Curve) values at CNN = 0.8891, SVM = 0.5978 and KNN = 0.5482. So from the AUC niai, it can be said that the CNN algorithm shows better performance than the comparison algorithms, namely SVM and KNN that have been used, because CNN has the largest AUC value or almost 100%. Because basically the AUC value has a value range between 50% (0.5) to 100% (1).

4.6 Test the Functionality of the Application

After all the programs are created and tested properly and then presented on the web server page as below, it can be seen that the skin cancer classification contains a Select File button to enter the image to be tested into the system as shown in Figure 4.5, the upload button to run the program that will display the original image being tested. On the classification results page, the original image of the tested image will appear along with the image processing process starting from image segmentation as shown in figure 4.5, to the results of classification using convolutional neural network (CNN), support vector machine (SVM), K-nearest neighbor (KNN) as shown in figure 7.

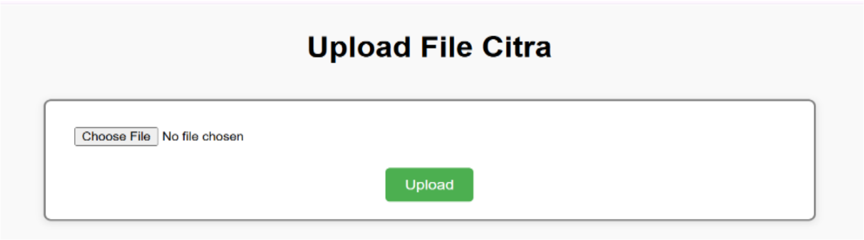


Figure 7. File Upload View

Figure 8 shows the original image display.

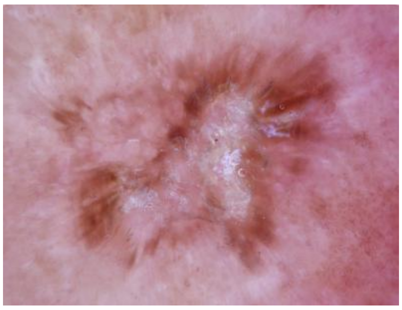


Figure 8. Original Image Display

Figure 9 shows the segmentation process on the images that have been selected for classification.

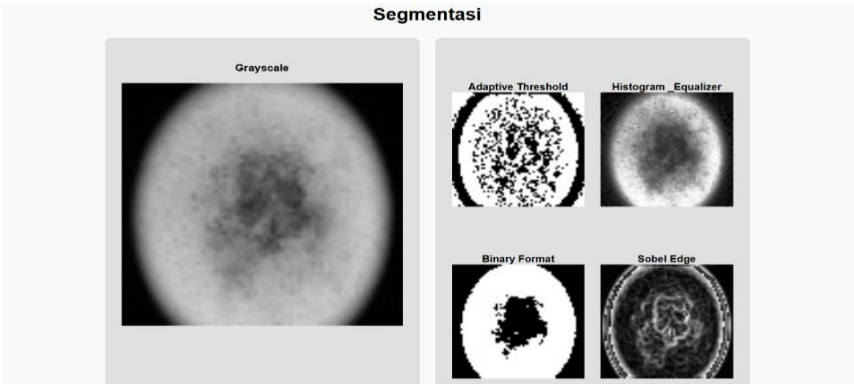


Figure 9. Segmentation Process

Figure 10 shows the predicted results of skin cancer using convolutional neural network (CNN), support vector machine (SVM), and K-nearest neighbor (KNN) methods.

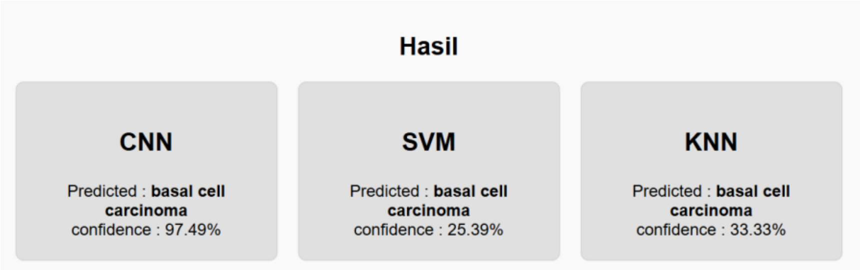


Figure 10. Classification Results

6. Conclusions And Suggestions

The implementation of the CNN, SVM, KNN model has a good performance in classifying skin cancer images, which are divided into nine image classes: Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented Benign, Seborheic Keratosis, Squamos Cell, Vascular Lesion.This study has shown the results of tests that have been carried out with an accuracy value of CNN 98.35%, SVM 91.17%, KNN 90.45%. In this study, it has succeeded in making and being able to classify skin cancer images, resulting in diagnostic instruments that are very useful for doctors.

6.1 Suggestion

There needs to be a development in the modeling of CNN, SVM and KNN programs that can be used to classify more images. Further research is expected to be able to use original skin cancer images from dermoscopy images as data input . It is hoped that after this research it can develop web design and features in the web that are more attractive.

References

[1] Chairani, M., Triana, D., Sudarsono, W., Kurniati, A., and Putri, S. R., “Accuracy of the use of dermoscopy in the diagnosis of scabies,” *Journal of Rape Medicine*, vol. 8, no. 1, pp. 48–55, 2022.
[2] Dian Ayu Nurlitasari, R. M., “Performance Analysis of Skin Cancer Classification System Using Convolutional Neural Network,” *JESCE (Journal of Electrical and System Control Engineering)*, vol. 2, Feb. 2022.
[3] Faruk, M., “Classification of Skin Cancer Based on Texture Features, Image Color Features Using SVM and KNN,” *Telematics*, vol. 13, no. 2, 2020.
[4] Fauzan Nuraulia Darmawan, E. P., “The classification system for skin diseases uses a website-based Convolutional Neural Network (CNN) method,” *Proceedings of the National Seminar on Research and Community Service*, LPPM 'Aisyiyah University Yogyakarta, Vol. 2, Sep. 28, 2024.
[5] Findriyani, R. A., “Classification of skin cancer based on benign and malignant image data using convolutional neural networks,” *JAMASTIKA*, vol. 3, Apr. 1, 2024.
[6] Desire, “Classification of Heart Disease Using the K-Nearest Neighbor Method,” *Indonesian Journal of Data and Science*, vol. 1, no. 1, pp. 6–10, 2020.
[7] Isnani, Y., “Classification of skin cancer using the K-Nearest Neighbor method,” Final Thesis Project, University of Technology Yogyakarta, 2021. (Also cited in: Ricky Yohannes, vol. 2, no. 2, Apr. 2022)
[8] Juliyanti, “Dermoscopy,” *Pandu Husada*, vol. 4, no. 2, 2023.
[9] Leonardus Sandy Ade Putra, “Improved Identification of Actinic Keratosis Skin Cancer Using a Combination of Extraction System with Classification Support Vector Machine,” n.d.
[10] Maulana, F. F., and Rochmawati, N., “Fruit image classification using convolutional neural network,” *Journal of Informatics and Computer Science (JINACS)*, vol. 1, no. 2, pp. 104–108, 2020. doi:10.26740/jinacs.v1n02.p104-108
[11] Naja Maskuri, M. H., “Application of the K-Nearest Neighbor (KNN) Algorithm for Stroke Prediction,” *Intech Scientific Journal: Information Technology Journal of UMUS*, vol. 4, no. 1, pp. 130–140, 2022.
[12] Ricky Yohannes, M. E., “Classification of skin cancer types using CNN SVM,” *Journal of Algorithms*, vol. 2, no. 2, pp. 133–144, Apr. 2022.
[13] Rizky Adawiyah, D. I., “Optimization of Skin Disease Detection Using the Support Vector Machine (SVM) and Gray Level Co-occurrence Matrix (GLCM) Method,” *Journal of Informatics and Information Systems*, vol. 14, no. 1, May 2022.
[14] Saifur Rohman Cholil, T. H., “Implementation of the K-Nearest Neighbor (KNN) classification algorithm for the classification of scholarship recipient selection,” *IJCIT (Indonesian Journal on Computer and Information Technology)*, vol. 6, no. 2, pp. 118–127, 2021.
[15] Sarwati Rahayu, S. S., “Performance Analysis of Multi-Class Skin Cancer Datasheet Classification Method Using KNN and HOG,” *JSAI*, vol. 9, n.d.

[16] Siskawati Rahayu, Y. Y., "Classification of Stroke Disease by Support Vector Machine (SVM) Method," *JINACS (Journal of Informatics and Computer Science)*, vol. 5, no. 3, 2024.
[17] Teresia R. Savera, W. H., "Early Detection of Skin Cancer Using K-NN and Convolutional Neural Network," *Journal of Information Technology and Computer Science (JTIIK)*, vol. 7, no. 2, pp. 373–378, Apr. 2020.
[18] Youllia Indrawaty Nurhasanah, I. A., "The Melanoma Cancer Type Recognition System in Imaging Using Gray Level Co-occurrence Matrices (GLCM) and K-Nearest Neighbor (KNN) Classifier," *MIND Journal*, vol. 5, no. 1, pp. 66–80, Jun. 2020.
[19] Yulia Farida Yahya, T. L., "Empowerment of health workers in primary health facilities in Sungsang District: introduction to skin cancer," *Journal of Community Service Humanity and Medicine*, vol. 2, no. 2, pp. 97–105, 2021. doi:10.32539/Hummed.V2I2.55