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Stand-Alone Melanoma Diagnostic System Using the Raspberry PI 4

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ABSTRACT: *Skin cancer, in general, is a growing threat to human health. Melanoma skin cancer is one of the most severe types of skin cancer in humans. In the initial stages, melanoma affects the skin in general, and it may develop and spread to other parts of the human body in its advanced stages. Early detection can reduce its severity and improve treatment outcomes. In this study, the proposed system includes image processing techniques and feature extraction by combining Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM), in addition to enhancing the extracted features with the diameter feature. A Support Vector Machine (SVM) model with a radial basis function (RBF) kernel was employed to train and predict the results of the test data on the Raspberry Pi 4 platform. The available International Skin Imaging Collaboration (ISIC) dataset of skin images was used in the training and testing of this system. The test results showed that the proposed system achieves high specificity (99.35%), medium sensitivity (75.35%), and comprehensive accuracy (93.71%).*

KEYWORDS: Melanoma, LBP, GLCM, SVM, Raspberry Pi 4

INTRODUCTION

The skin, which makes up 16% of the body weight and is the human body's exterior organ, is in the position of protecting the interior organs. Skin cancer is one of the disorders that may infect the skin and has the potential of causing a variety of injuries or infections. The sun's ultraviolet (UV) radiation is the most affecting factor to cause skin cancer[1]. However, when skin pigment is lost, some UV-sensitive particles, such as DNA, absorb UV radiation that penetrates the epidermis. The possibility of a change in DNA structure as a result of this absorption raises the possibility of skin cancer[2].

Melanoma is considered the most dangerous and deadly type of skin cancer, and the number of its infections is increasing all over the world. Although research indicates that melanoma targets older men in the age group over (65) years, it may appear in women and young people who range in age between (25-39) years. Melanoma is more common in people with fair skin than those with dark skin. The primary risk factor for melanoma is the exposure to ultraviolet radiation from the sun, although family history, genetics, environmental factors, and weakened immunity can also contribute to its development[3]. Early detection and treatment of melanoma are crucial for reducing the risk of its progression and improving health outcomes. This study aims to explore the potential of image processing and machine learning techniques for establishing early melanoma detection and classification.

LITERATURE REVIEW

The researchers used several advanced, modern, and important methods to diagnose skin cancer. Some of these scientific papers are reviewed here. Most modern methods refer to the use of computers as a common approach to detect skin cancer in general and melanoma in particular.

In 2017, JC Kavitha et al.[4] suggested different methods to extract features from dataset images. Gray Level Co-occurrence Matrix (GLCM) is used to describe the global texture features, while Speeded Up Robust Features (SURF) is used to describe the local texture features. The dataset used in this paper contains 250 dermoscopic images, divided into 150 for training and 100 for testing. Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) are used as classifiers for melanoma classification. The best accuracy was 87.3% when using SURF feature extraction and SVM as a classifier.

In 2019, Seeja R D[1] Suresh A[2][5] proposed segmenting the skin lesion using a convolutional neural network (CNN)-based U-net algorithm. Used many ways for feature extraction: local binary pattern (LBP), edge histogram (EH), histogram of oriented gradient (HOG), and the Gabor method to describe the texture and shape features of an image. Used SVM, Random Forest (RF), KNN, and Naïve Bayes (NB) as classifiers to detect melanoma. The results of comparisons of classification methods showed that the best accuracy was 85.19 when using an SVM classifier.

In 2020, Ginni Arora et al.[6] designed a computer-aided detection system to diagnose skin cancer using images in MATLAB. Combined two methods of feature extraction: bag-of-feature and speeded up robust features. The database used for training PH2 contains 100 images, including 50 cancer images and 50 non-cancerous images. In this paper, they used quadratic SVM for classification and predicted the results. The results' accuracy was 85.7%.

In 2021, Marriam Nawaz et al.[7] proposed a faster region-based convolutional neural network for feature extraction from data images. The dataset used in ISIC-2016 contains 1279 images, of which 248 were malignant melanoma images and 1031 were benign. The classification method for malignant and benign melanoma used an SVM classifier. The accuracy of the results was 89.1%.

In 2022, A. Alsarraf O. Ucan [8] proposed a method for analyzing the skin data images for enhanced melanoma detection. Segmentation using K-means clustering and thresholding was the first step in this four-step process. The second is a pre-processing step including the median and Sobel operator filters. In third step, LBP and GLCM were employed for feature extraction. Finally, SVM was used as a classifier for melanoma detection. In this paper, ISIC dermoscopy images were utilized. This technique had a 93.28% accuracy rate. It was suggested that they employ a mobile app (like WhatsApp) to transmit the clinical images to the dermatologist for examination.

In 2022, M. Kartal Ö. Polat [9] suggested a deep residual learning model called ResNet101 architecture for melanoma detection from dermoscopic images. The ISIC 2017 dataset consists of 3297 dermoscopic images, which were divided into 2637 images for training and 660 images for testing. The ResNet101 showed a maximum accuracy of 91.36%.

The purpose of this study is to design a system that detects melanoma in its early stages and to provide medical care that enhances the health reality of human life. Using the Raspberry Pi 4 to function as an integrated, stand-alone medical device unit by providing it with a digital microscope camera to take pictures of new suspected cases, process them with the appropriate operations, and give the correct diagnosis. The use of appropriate techniques in image processing, which aim to improve the images and show the important features through which the distinction and detection of melanoma can be achieved.

METHODOLOGY

The proposed system in this study has been designed according to specific steps as shown in Figure 1, including:

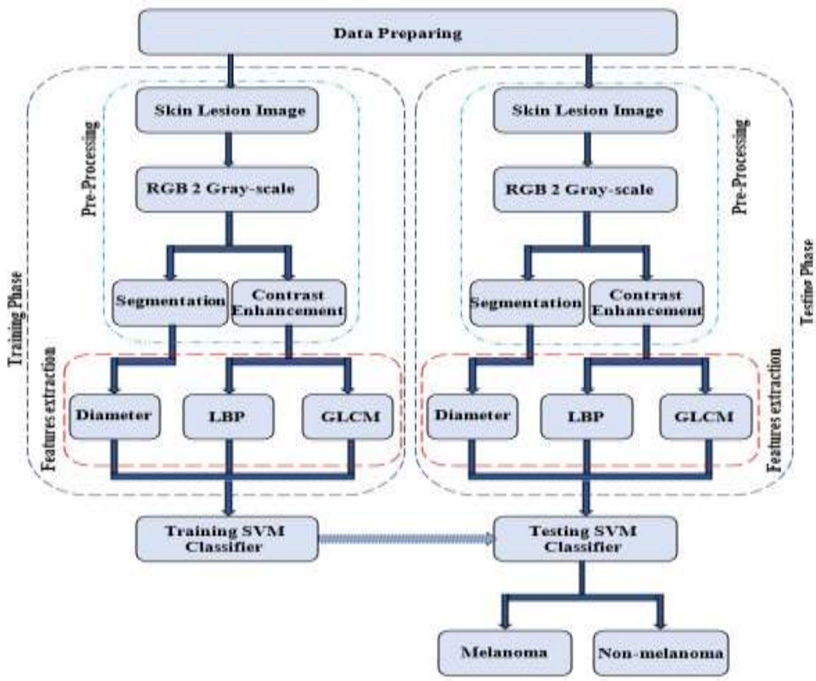

Figure 1. **block diagram of proposed system.**

INPUT DATA

The database used in this work contains Dermatoscope images of different sizes that have been unified using digital image processing.
Unsharp masking, this is one of the most popular image processing techniques for sharpening images. This high-pass filter reduces low-frequency noise[10].
Bicubic interpolation: is a complex technique used for image resizing; it produces the best results for soft details. It uses a 4x4 grid of adjacent pixels to estimate a pixel's value in the new image. The interpolation value is calculated using equation (1), as in[11].

$$\upsilon(x, y) = \sum_{i}^{3} \sum_{j=0}^{3} a_{ij}\, x^{i} y^{j} \tag{1}$$

PRE-PROCESSING STAGE

Image pre-processing involves several steps that are utilized by using a set of image processing methods and techniques to make the image more suitable before features extraction and before being used by the training model.
RGB to Grayscale conversion, gray-scale conversion is the first stage in many image processing techniques, since it decreases the amount of information in the image. However, the majority of important feature-related information is preserved, such as edges, regions, blobs, and junctions. Feature identification and processing algorithms then commonly work on the converted greyscale version of the image[10].

- Contrast enhancement, the contrast between skin and the lesion is very poor in many images, and it will not be easy to distinguish the details that lead to a correct diagnosis of melanoma. Therefore, to increase the contrast, histogram equalization is applied. Histogram equalization enhances contrast for brightness values near histogram maxima and reduces contrast for brightness values close to histogram minima. The goal is to generate an image that is uniformly distributed over the whole brightness scale[11].
- Average filter, the average filter, also known as the arithmetic mean filter, is a low pass filter (LPF). It is a type of digital image filtering technique used in noise reduction or image smoothing directly over the spatial domain. It works by replacing the value of each pixel in the original image with the average value of the pixel and its neighboring pixels within a specified window or kernel size of m x n[12].
- Morphological operations, use small matrices called structuring elements to modify image pixels[13]. Erosion makes objects smaller and thinner, while dilation makes them larger. The opening procedure removes small objects, smooths larger object edges, and separates connected objects. The closing procedure preserves outer object borders while closing gaps and holes and can combine separated objects that are close. These operations are useful in image segmentation to isolate and extract specific objects or features in an image. Note that the amount of erosion or dilation of the image is determined by the size and shape of the structural element, not the original image[14]. Morphological reconstruction is a more advanced operation. It is used for image segmentation and enhancement. The process

involves repeatedly dilating a marker image (usually a part of the original image) using a mask image (usually a modified version of the original image) until the dilated image stabilizes. This helps restore or enhance specific regions of interest in the image[15].

- Segmentation, the study of segmenting images into meaningful parts for specific purposes is known as image segmentation. In the simplest cases, the segmented image would be a binary image with just these two classes (foreground and background)[16]. In this study using the Otsu's thresholding for segmented the skin lesion images. Otsu's method identifies the threshold that produces the least amount of variation within each class of thresholded black and white pixels. Specifically, this method chooses the threshold that causes the foreground and background pixels to cluster together most tightly. Otsu's approach is optimal because it maximizes the between-class variance, a standard indicator in statistical discriminant analysis. It is assumed that suitably thresholded classes will have different pixel intensity values, and that the best (optimal) threshold will be the one that provides the greatest degree of separation across classes. In addition to being the most effective approach, Otsu's technique also has the advantageous feature of being based only on calculations made using an image's histogram[13][10].

FEATURE EXTRACTION

The texture of an image is the spatial distribution of grey levels over the pixels, which is used to identify objects or regions of interest[17]. In this work, various techniques for extracting features from images of skin lesions were combined, these are mentioned in the following:

- Local Binary Pattern (LBP), it is a technique for analyzing textures that describes an image's local structure. LBP operates by comparing each pixel's intensity value with the intensity values of its 3×3 surrounding pixels. In particular, the LBP operator assigns each pixel in the image a binary code by comparing the intensity of the central pixel with the intensity values of its neighbors. Any pixel is given a value of 1 if the intensity of the center pixel is higher than or equal to the intensity of a neighboring pixel; otherwise, it is given a value of 0[18].
- Gray Level Co-occurrence Matrix (GLCM), it is used to analyze image texture. It describes the probability of two pairs of gray levels occurring together in an image, allowing for the extraction of texture features to differentiate between various textures. This study uses GLCM to extract four important different features[19], contrast, correlation, energy, and homogeneity.
- Diameter, it is a significant feature for detecting skin cancer. Lesions with a diameter greater than 6mm are indicative of melanoma, while those with a smaller diameter are non-melanoma[20].

CLASSIFICATION

Machine learning is a branch of computer science that aims to create and develop a set of algorithms that can find patterns in already-existing data and use those patterns to predict results for new data[21]. As a simple definition of the SVM, it is a supervised learning method that requires training and testing data to set it up[22]. SVM is used to classify data by finding the best hyperplane that separates all data points of one class from those of the other. The two hyperplanes that pass through one or more data points are known as boundary planes. The best hyperplane is the one with the maximum margin between the two classes, which is the maximum width of the parallel boundary planes to the hyperplane. The data points that are at the closest proximity to the separating hyperplane, on the margin's edge, are the support vectors. Strong, easy to use, and very effective are features that can best describe the SVM[23][24].

PERFRMANCE EVALUATION METRICS

There are several different methods of evaluating performance, the aim of which is to evaluate the performance of different tasks. In this study, three commonly used methods were selected for evaluating work performance[25].

- Accuracy (ACC), This is used to evaluate the performance of classification results for both melanoma and non-melanoma categories. Equation (2) can be used for calculating the accuracy:

$$\text{Acc} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

- Sensitivity (SEN), It is used to measure the model's ability to correctly diagnose melanoma. Equation (3) shows how to calculate the sensitivity:

$$\text{SEN} = \frac{TP}{TP+FN} \tag{3}$$

- Specificity (SEP), Which is used to measure the model's ability to correctly diagnose non-melanoma. Equation (4) that can be used for calculating specificity is:

$$\text{SEP} = \frac{TN}{TN+FP} \tag{4}$$

Where is:
TP refers to correctly diagnosed melanoma cases (True Positive),
FP is the diagnosed cases with melanoma incorrectly (False Positive),
TN is the diagnosed cases with non-melanoma correctly (True Negative),
FN is the diagnosed cases with non-melanoma incorrectly (False Negative).

EXPERMINTAL WORK

The designed system has four main stages, as follows:

- The dataset preparing stage.

- SVM training stage.
- SVM testing stage and displaying the results.
- Implementing the previous stages on the Raspberry Pi 4 platform.

The following will explain each stage separately:

DATASET PREPARING

The database used in this study consisted of 2357 high-resolution digital images of the Dermatoscope for malignant and benign tumors with a (.jpg) extension. These images have been collected by the International Skin Imaging Collaboration (ISIC) from the Kaggle website[26]. 2038 images are randomly selected and separated into 1433 training images and 605 test images; the train-to-test data ratio is chosen to be 70% to 30%. The training database contains 343 images diagnosed with melanoma and 1090 images diagnosed with non-melanoma. The test database contained 110 images diagnosed with melanoma and 495 images diagnosed with non-melanoma. The images in the database are of different sizes and aspect ratios, ranging from 600 * 450 to 6708 * 4439. All images in the database have been resized to 1200 * 900. The aspect ratio for this size is 4/3. Database images are unified due to their use on the Raspberry Pi 4 platform memory, which demands limiting their dimensions and being able to calculate the total memory space needed. All database images have been unified through the following two sub-steps:

- Unsharp masking, using the unsharp masking (3 x 3) to enhance the borders of the lesion and to distinguish it from the skin.
- Image resizing, using the bicubic interpolation technique to resize the image while preserving fine details of the lesion and to reduce the loss of important information in the images by the resizing of them. Saving the resized images in a new file with the same extension format (.jpg).

SVM TRAINING STAGE

The training database is imported and converted into grayscale images to facilitate handling, and then the image entry is divided into two branches: Using the histogram equalization technique to balance the contrast in the images. These images are directly fed into the LBP and GLCM algorithms to extract texture features from them. On the other hand, the other branch is to enter images of training data using a low-pass filter. In this study, the average filter is used to remove and reduce the noise associated with the image of the skin lesion, such as hair, air bubbles, reflections of skin surface cells, etc. The images obtained from the average filter undergo a set of morphological operations. The process of isolating the lesions in the images is done by using structural elements and morphological operations. These processes helped to improve and refine the borders of each lesion in the images. The Otsu’s thresholding technique is used to segment the foreground (the skin lesion) from the background in the image. The resulting segmented image feature diameter is calculated to enhance the algorithms used in feature extraction. Figure 2 shows the result of applying the processes of step 2 on the skin lesion images.

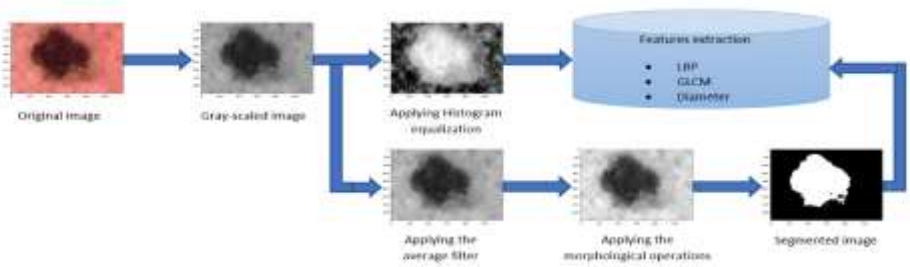

Figure 2. The image results from the pre-processing techniques

SVM TESTING STAGE

In the training phase, important features are extracted from the image dataset, capturing relevant information for melanoma detection. These features are then used to train the SVM model using the RBF kernel, which enables effective mapping of the features into a higher-dimensional space. In the testing phase, the features extracted from the test images are input into the trained model. The SVM model, utilizing the RBF kernel, transforms the test features into the same higher-dimensional space as in training. By measuring the distance of the new data points from the hyperplane, the trained model predicts the class of the test image based on the shortest distance, assigning it to either the melanoma or non-melanoma category.

RASPBERRY PI SYSTEM

The proposed system was embedded on the Raspberry Pi 4 to be a stand-alone system by providing it with an input unit (mouse and keyboard) and a display output unit, in addition to providing it with a USB digital microscope camera. Figure 4. shows the Raspberry Pi 4 stand-alone system for melanoma diagnosis.

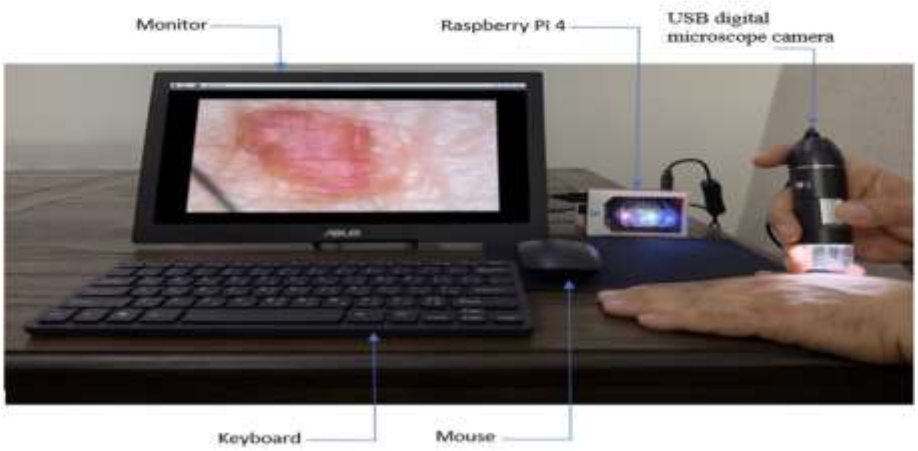

Figure 3. Raspberry Pi 4 stand-alone system for melanoma diagnosis.

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RESULTS

Following are the outcomes of the suggested system for diagnosing melanoma in this section:

Table 1. The results of testing dataset images.

Testing (605) diagnosed images	SVM with RBF kernel	
	Melanoma (110)	Non-melanoma (495)
Classified as melanoma	TP (107)	FN (35)
Classified as non-melanoma	TN (460)	FP (3)
Specificity	99.35%	
Sensitivity	75.35%	
Accuracy	93.71%	

As shown in Table 1, 110 images were diagnosed as melanoma, and 495 images were diagnosed as non-melanoma. The correct diagnosis for melanoma is TP, while FN is an incorrect diagnosis. The correct diagnosis for non-melanoma is TN, while FP is an incorrect diagnosis. The specificity of the results was 99.35%, the sensitivity was 75.35%, and the accuracy of the results in general was 93.71%. This accuracy indicates the success of training the model and its ability to distinguish between melanoma and non-melanoma. Figure 5. Shows the confusion matrix of the results.

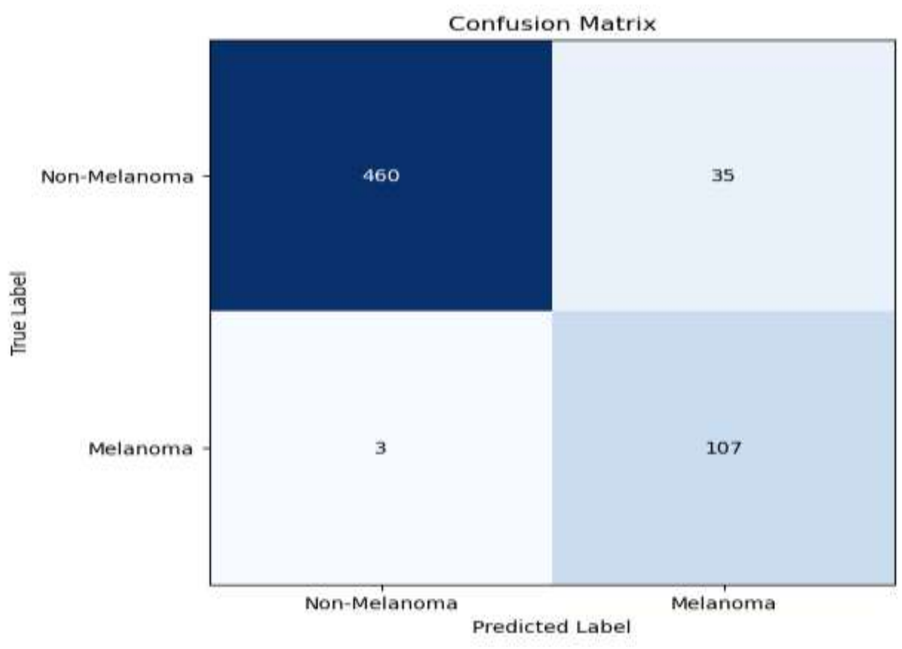

Figure 4. The confusion matrix of the system results.

CONCLUSIONS AND FUTERE WORKS

The melanoma diagnosing system proposed here gives a good accuracy of 93.71%, so it can be used to assist doctors in easing diagnosis matters. The image processing techniques used for unifying the size of all dataset images provide easy memory size calculation and manipulation. Feature extraction elements kept the important features that are needed for diagnosis mostly unchanged to get a better diagnosis. The accuracy can be increased by adding more features and by using more dataset images for training. The system can be used as a stand-alone diagnostic apparatus with the following hardware additives to the Raspberry Pi 4: a USB digital microscope camera to get lesion images, a mouse, a keyboard, and a monitor. The diagnosing code was written in Python high level language on the computer and then copied to the Raspberry Pi 4's internal memory.

This study could be used for diagnosing other types of skin cancer, such as basal cell carcinoma and squamous cell carcinoma. This may demand changing the features used here so as to get the best features that characterize these skin cancer types.

References

[1] A. Rotte and M. Bhandaru, *Immunotherapy of melanoma: towards clinical application*. Springer International Publishing AG, 2016. doi: 10.1007/978-3-319-48066-4.

[2] P. Gnagnarella *et al.*, "Vitamin d receptor polymorphisms and cancer," *Advances in Experimental Medicine and Biology*, vol. 1268. pp. 53–114, 2020. doi: 10.1007/978-3-030-46227-7_4.

[3] D. J. L. Wong and A. Ribas, *Melanoma*, vol. 167. Springer International Publishing, 2016. doi: 10.1007/978-3-319-22539-5_10.

[4] J. Kavitha, S. A, and N. D, "Melanoma Detection in Dermoscopic Images using Global and Local Feature Extraction," *International Journal of Multimedia and Ubiquitous Engineering*, vol. 12, no. 5. pp. 19–28, 2017. doi: 10.14257/ijmue.2017.12.5.02.

[5] R. D. Seeja and A. Suresh, "Deep learning based skin lesion segmentation and classification of melanoma using support vector machine (SVM)," *Asian Pacific J. Cancer Prev.*, vol. 20, no. 5, pp. 1555–1561, 2019, doi: 10.31557/APJCP.2019.20.5.1555.

[6] G. Arora, A. K. Dubey, Z. A. Jaffery, and A. Rocha, "Bag of feature and support vector machine based early diagnosis of skin cancer," *Neural Comput. Appl.*, vol. 34, no. 11, pp. 8385–8392, 2022, doi: 10.1007/s00521-020-05212-y.

[7] R. Zhang, "Melanoma Detection Using Convolutional Neural Network," *2021 IEEE Int. Conf.*

Consum. Electron. Comput. Eng. ICCECE 2021, no. Iccece, pp. 75–78, 2021, doi: 10.1109/ICCECE51280.2021.9342142.

[8] A. M. M. Alsarraf and O. N. Ucan, "Detection and Classification of Melanoma by Analysis of Skin Lesions Using Teledermatology," in *2022 8th International Conference on Contemporary Information Technology and Mathematics (ICCITM)*, 2022, pp. 341–346.

[9] M. S. Kartal and Ö. Polat, "Detection of Benign and Malignant Skin Cancer from Dermoscopic Images using Modified Deep Residual Learning Model," *Artificial Intelligence Theory and Applications*, vol. 2, no. 2. pp. 10–18, 2022.

[10] A. Vyas, S. Yu, and J. Paik, *Fundamentals of digital image processing*. John Wiley & Sons, Ltd Wiley, 2018. doi: 10.1007/978-981-10-7272-7_1.

[11] V. H. and R. B. M. Sonka, *Image processing, analysis, and machine vision. Cengage Learning*. 2014.

[12] S. Patnaik, I. K. Sethi, and X. Li, "Advanced Image and Video Processing Using MATLAB," *High-Performance Computing Infrastructure for South East Europe's Research Communities*, vol. 2. pp. 93–98, 2014. [Online]. Available: http://link.springer.com/10.1007/978-3-319-01520-0

[13] R. . Gonzales, R.C, & Woods, *Digital Image Processing*, 4th Editio. Pearson Education Limited, 2018.

[14] D. Chudasama, T. Patel, S. Joshi, and G. I. Prajapati, "Image segmentation using morphological operations," *Int. J. Comput. Appl.*, vol. 117, no. 18, 2015.

[15] J. Zhang, Z. Guo, T. Jiao, and M. Wang, "Defect detection of aluminum alloy wheels in radiography images using adaptive threshold and morphological reconstruction," *Applied Sciences (Switzerland)*, vol. 8, no. 12. 2018. doi: 10.3390/app8122366.

[16] D. R. Okada and R. Blankstein, *Digital Image Processing for Medical Applications*, vol. 52, no. 4. 2009. doi: 10.1353/pbm.0.0123.

[17] B. K. Singh and G. R. Sinha, *Machine Learning in Healthcare: Fundamentals and Recent Applications*, 1st editio. CRC Press, 2022. doi: https://doi.org/10.1201/9781003097808.

[18] A. Gautam and B. Raman, "Skin cancer classification from dermoscopic images using feature extraction methods," *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, vol. 2020-Novem, pp. 958–963, 2020, doi: 10.1109/TENCON50793.2020.9293863.

[19] M. Ramachandro, T. Daniya, and B. Saritha, "Skin Cancer Detection Using Machine Learning

Algorithms," *3rd IEEE Int. Virtual Conf. Innov. Power Adv. Comput. Technol. i-PACT 2021*, pp. 5–9, 2021, doi: 10.1109/i-PACT52855.2021.9696874.

[20] E. M. Senan and M. E. Jadhav, "Analysis of dermoscopy images by using ABCD rule for early detection of skin cancer," *Glob. Transitions Proc.*, vol. 2, no. 1, pp. 1–7, 2021, doi: 10.1016/j.gltp.2021.01.001.

[21] G. Wu, D. Shen, and M. R. Sabuncu, *Machine Learning and Medical Imaging*. 2016. doi: 10.1016/c2015-0-00754-7.

[22] J. Fix, H. Frezza-Buet, M. Geist, and F. Pennerath, "Machine Learning .pdf." John Wiley & Sons, Inc., Canada, 2015.

[23] G. R. Kumar Singh, B. & Sinha, *Machine Learning in Healthcare Fundamentals and Recent Applications*, 1st Editio. UK: CRC Press, 2022. doi: 10.1201/9781003097808.

[24] D. Keerthana, V. Venugopal, M. K. Nath, and M. Mishra, "Hybrid convolutional neural networks with SVM classifier for classification of skin cancer," *Biomed. Eng. Adv.*, vol. 5, no. November 2022, p. 100069, 2023, doi: 10.1016/j.bea.2022.100069.

[25] V. Ruthra and P. Sumathy, "Color and Texture based Feature Extraction for Classifying Skin Cancer using Support Vector Machine and Convolutional Neural Network," *Int. Res. J. Eng. Technol.*, pp. 502–507, 2019, [Online]. Available: www.irjet.net

[26] "Skin Cancer ISIC | Kaggle." https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic (accessed Apr. 01, 2023).