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Comparison Feed Forward Back Propagation Networks (FFBPNs) with Support Vector Machine (SVM) for Diagnosis of Skin Cancer Based on Images

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ABSTRACT

Skin cancer is a type of malignancy responsible for 70 percent of overall skin cancer-related death worldwide. In previous years, doctors relied on visual examination to identify suspicious pigmented lesions that could indicate skin cancer. The purpose of the research: Uses of AI include detecting skin cancer of all types more quickly and improving the efficiency of diagnostic radiology, which will reduce the rate of inaccurate diagnosis of cancer and diagnose skin cancer more accurately by dermatologists. The method used in this paper is artificial neural network technology implemented for detecting skin cancer and the watershed segmentation method for segmentation. The features extraction for an extracted segment. The features extracted are shaped and Gray-Level Co-Occurrence Matrix. The extracted feature is used for classification. The classifiers are Support Vector Machine and Feed forward Back Propagation applied in Matlab enivermental and an image processing technique on a set of photographs collected from several websites, including the Kaggle web. The implementation of code for the detection of skin cancer by using data as 100 images 50 no cancer and 50 is cancer; the result shows successful implementation for the detection of cancer in FFBP classifiers 45 and 2 is bad detection, as well as in SVM classifier 49 with 1 is bad diagnostic. The conclusion shows that the SVM classifier provides results for the classification of skin lesions with 98% accuracy and an FFBP of 96 %. The conclusion of this study is helping people with skin cancer undergo a CT scan.

1. INTRODUCTION

Artificial intelligence is the ability to make computers or machines learn to solve problems that require human effort [1]-[6]. Advances in computing power have made it easier to analyze large amounts of data quickly, consistently, and accurately [7]. This has enabled healthcare scientists to use AI on large, complex data sets in a way that improves decision-making, diagnosis, and treatment by discovering patterns in patient data, as well as diagnosing medical images such as X-rays, CT scans, and MRIs [8]-[11].

The basic unit of an AI system is the "neural network." For example, a computer system is trained by absorbing and analyzing hundreds of thousands of sets of similar readings and images [12]-[16]. The computer then becomes saturated with expertise in looking at a question under study for a particular disease or medical condition [17]-[21]. The result is an AI system that can read a simple test, detect a disease condition, diagnose a particular image, and predict potential problems in the future, thus helping doctors reach the right decision and take the appropriate treatment [22]-[26]. Artificial intelligence is achieving great success in the medical field, and scientists expect that artificial intelligence techniques will lead to the advancement of the healthcare sector over the next few years, as artificial intelligence contributes significantly to diagnosing skin cancer more accurately than dermatologists [27]-[31]. Skin cancer is a type of malignancy responsible for 70% of every

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skin cancer-related death worldwide. In previous years, doctors relied on visual examination to identify suspicious pigmented lesions that could be indicative of skin cancer [32]-[36].

Thus, it contributes to the early recognition of dermatomyositis, which improves the prognosis of melanoma, provides rapid intervention, and significantly reduces the cost of treatment. However, the difficulty is to find and quickly prioritize these lesions, given the large volume of pigmented lesions that often need to be biopsied and evaluated [31][32][37]. Many researchers have used artificial intelligence to detect skin cancer, such as Prachya Bumrungkun (2018) [38]. Suggest an image segmentation scheme based on Vector Machine (SVM) support and active Snake contour to study and analyze cancer image features, which include asymmetry, compact index, fractal dimension, border irregularity, color and diameter variance, and edge discontinuity, to analyze medical images of melanoma patients, which contribute to the detection of skin cancer. The results showed that using SVM to help find the appropriate parameters for the Python algorithm was good. Agung W. Setiawan (2020) [39] presented Simple Image Processing and Image Contrast Enhancement Techniques for melanoma detection, contrast enhancement with CLAHE and MSRCR, and contrast improvement with CNN. The result showed that when compared with MSRCR, CLAHE was additionally favorable in improving the color image. Thus, the accuracy of melanoma detection using CNN, besides the improved CLAHE dataset, provides the same precision in training and validations. Yessi Jusman (2021) [40] The Artificial Neural Networks method was introduced with Multi-layer Perceptron training, custom convolutional neural networks, and VGG-16 of melanoma grading using a large dataset obtained for melanoma, HAM10000. Then, the presentation of every trained model will be compared and analyzed regarding computational time and classification accuracy. The results showed that the VGG-16 model gave the best classification accuracy in terms of test time and that the two models of VGG-16 and the custom CNN model were much faster than the Multi-layer Perceptron. Burcu Bılgıç (2021) [41] This study presented a comparison between breast and skin cancer using deep learning methods, one of the artificial intelligence techniques, where the disease data obtained were classified into benign and malignant deep learning methods. The classification was done using the Convolutional Neural Networks (CNNs) algorithm. The information is also separated into benign and malignant; in conclusion, the information was analyzed using the logistic regression technique, and the results were compared using success charts for both types of cancer, showing precision and loss graphs.

This research aims to use artificial neural networks to detect skin cancer, reduce the inaccurate cancer diagnosis rate, and compare them.

2. METHOD

2.1. Skin Cancer

Skin cancer is defined as a growth of tumors in the skin, and many kinds of skin cancer depend on the type of skin cell in which the tumor originates [42]-[46] that is shown in Figure 1.

The most common kinds of skin cancer are as follows:

1. Melanoma arises in melanocytes, which give the skin its colour.
2. Squamous cell carcinoma arises in the flat squamous cells that make up the top layer of the skin.
3. Basal cell carcinoma, which arises in basal cells in the upper layers of skin below the squamous cell.
4. People who have had BCCs are prone to develop it again in their lifetime.

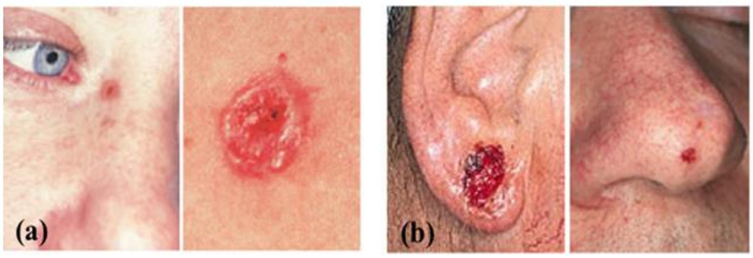


Figure 1. A patch red (a) and sore open (b) types for basal-cell carcinoma

2.2. Causes of skin cancer and symptoms

The main reason for skin cancer is prolonged exposure to the sun and its ultraviolet rays. Generally speaking, those with fair skin and blond hair are more vulnerable than those with dark skin and black hair. All UV radiation exposure, including radiation therapy, indoor tanning beds, and occupational radiation exposure, increases the risk of acquiring skin cancer. Moles on the body can also develop into melanoma skin cancer, so it's important to check them frequently for changes in color, size, or shape [47][48]. Additionally, skin cancer might develop for unknown reasons. Although having one or more of these factors may raise the risk of developing skin cancer, having them does not guarantee that a person will get the disease [49]-[51]. The two most frequent signs of melanoma skin cancer are either a new mole or a change in an existing mole, particularly if the color of the mole changes or if its diameter, height, or border asymmetry increases. Although less often, bleeding, itching, ulceration, and discomfort in a mole require attention. A change in an existing growth, a wound that does not heal, or a new growth on the skin [52]-[56].

2.3. Artificial Neural Network

A mathematical model called artificial neural networks (ANN) attempts to mimic the structure of its biological counterparts. McCulloch and Pitts devised a simple depiction of the neuron in 1943 [57]. An artificial neuron consists of three straightforward rules: multiplication, summation, and activation. It is a straightforward mathematical representation of an artificial neural network. The network outlet is the total of the mixture multiplied by weights with the bias transient through the transfer function, where all neuron inputs are multiplied by weight and coupled with bias [58].

2.3.1. Feedforward Neural Networks

Forward Neural Networks (FFNNs) are artificial neural networks between nodes. There are two training of artificial neural networks.

2.3.1.1. Single-Layer Perceptron

One of the instructions for artificial neural networks is a single-layered neural network. The neurons are arranged in the form of layers. This type containIraqs one layer of inputs fully connected to the output layer. This means the network is firmly a feed-forward, as illustrated in Figure 2.

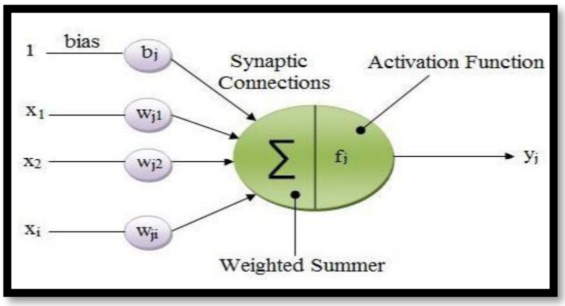


Figure 2. The block diagram for artificial neural networks

2.3.1.2. Multi-Layer Perceptron

This is another type of perceptron that arranges itself using the existence of one or greater hidden layer (one or more) between the input layer and the output layer. The hidden neurons are referred to as computation nodes, which are correspondingly used to interfere between the external input and the network output in some helpful way. The network is applied to extract information of a high degree. This type of neural network is used to solve complex problem [59].

2.3.2. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a popular classifier that is used for accurate and efficient classification [60]. In computer-aided diagnosis systems used by skin cancer specialists to detect melanoma early and save lives, SVM exhibits great accuracy in classifying clinical photos of melanoma (skin cancer). They seek to create a low-cost, portable medical device with a built-in, real-time, SVM-based diagnosis system for primary care for the early detection of melanoma. Results show a high % classification accuracy of 98% when an optimized SVM classifier is used in this study. Using image processing techniques based on active contour segmentation, Local Binary Pattern, and SVM classifier, the suggested study demonstrates an improvement in detecting melanoma skin cancer at various stages. The main goal of the proposed study is to extract the area, perimeter, mean (R), mean (G), mean (B), and texture properties from skin images. This makes it possible to analyze the melanoma spot analysis and provides direction for the cancer's spread. The features are adjusted for skin image size to remain the same regardless of how the image's properties change. The key goal is that the same image's features remain consistent regardless of the image's orientation, size, or location.

3. Proposed METHOD

A general step of the methodological system's coverage of the diagnosis of melanoma skin cancer may be seen in the several steps covered. The block diagram depicts the methodology system's organizational structure for this study, as seen in Figure 3. The tests were conducted using the MATLAB platform and an image processing technique on a set of photographs collected from several websites, including the Kaggle web. The image processing program processes the images, analyzes their attributes, and categorizes them into benign and malignant categories. The collected images suffer from noise and have inconsistent backdrop illumination because they were taken with general-purpose digital cameras. In addition to these problems, some lesions have hair growing over them, complicating identification. Utilizing computer vision and pattern analysis tools to diagnose early melanoma skin cancer is more efficient than using a standard biopsy. The advantages over conventional methods were primarily in the two parameters of cost and time, which were more efficient and required less money and time for system detection and evaluation. The experiment dataset in FFBPN and SVM is shown in Tables 1 and 2, and the Performance of Classification FFBPN and SVM are shown in Table 3. These processes follow the steps of image acquisition and processing through the segmentation stage and feature extraction by GLCM, which defines functions that characterize an image's texture by calculating how often pairs of pixels with specific values and in a specified spatial relationship occur in an image.

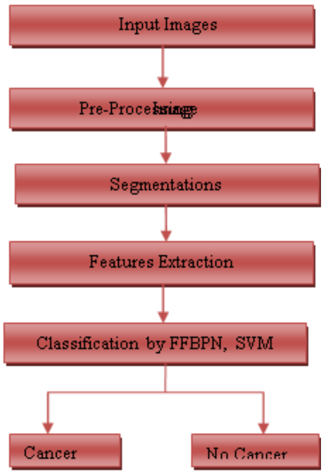
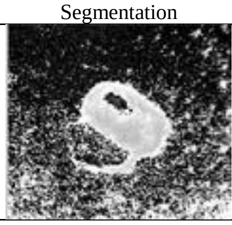
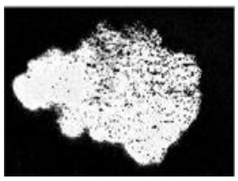


Figure 3. Schematic Diagram of Methodology System

Table 1. Stages of Diagnosis Skin Cancer

Image	preprocessing	Segmentation	Cl
			Basel cell carcinoma
			Melanoma
			Basel cell carcinoma

.

Table 2. Feature Extraction using SVM classifier

Image No. Test	Contrast	Correlation	Energy	Homogeneity	Mean	Standard Deviation	Entropy
Image 1	0.9444	0.9073	160.4396	29.2592	6.7072	530.9356	7.4283
Image 2	0.9167	0.8613	188.0580	18.6677	6.2291	311.1933	3.9516
Image 3	0.0010	0.0009	0.1218	0.0561	0.0071	1.7393	0.0020
Image 4	0.9661	0.9379	155.6421	21.4200	6.2604	380.6726	7.0144
Image 5	0.9343	0.8810	134.4072	45.8711	7.1042	902.1955	3.0269
Image 6	0.0009	0.0008	0.1266	0.0389	0.0073	1.0053	0.0031

Table 3 . Feature Extraction using FFBP classifier

Image No. Test	Contrast	Correlation	Energy	Homogeneity	Mean	Standard Deviation	Entropy
Image 1	0.9554	0.9114	159.976	28.9942	6.8802	531.0231	7.4313
Image 2	0.9231	0.8582	188.876	18.8657	6.3291	311.0991	3.9610
Image 3	0.0008	0.0018	0.10454	0.10665	0.0061	1.82311	0.0019
Image 4	0.9421	0.9410	155.642	22.2320	6.3014	381.2067	7.0154
Image 5	0.9765	0.8791	135.026	45.9981	7.0992	902.2045	3.0297
Image 6	0.0010	0.0019	0.19563	0.04109	0.0105	1.0061	0.0029

4. Results And Discussion

The results of the implementation of code for the detection of skin cancer were obtained by using data such as 100 images, 50 no cancer, and 50 are cancer. The results show successful implementation for the detection of cancer in the FFBP classifier, and 45 and 2 are bad detection, as well as in SVM classifier 49, with 1 being a bad diagnostic, as shown in Tables 4 and 5. FFBPN and SVM Classification Performance (Accuracy, Sensitivity, Specificity) are shown in Table 6.

Table 4 . The experiment dataset in FFBPN

Diagnosis	No. Cancer	Cancer
No. Cancer	48TP	2FP
Cancer	5 FN	45 TN

Table 5 . The experiment dataset in SVM

Diagnosis	No Cancer	Cancer
No Cancer	49 TP	1FP
Cancer	2 FN	48TN

Table 6. FFBPN and SVM Classification Performance

% Responses	SVM	FFBPN
Sensitivity	90.56%	96.07%
Specificity	95.47%	97.95%
Accuracy	98%	96

Accuracy is defined as a ratio for correct information during diagnosis to all information as equation (1):

$$Accuracy\ (\%) = \frac{Number of correct\ data}{Number of all\ data} \tag{1}$$

Sensitivity is defined a success rate for a person diagnosed with Cancer as equation (2)

$$Sensitivity\ (\%) = \frac{TP}{TP + FN} * 100 \tag{2}$$

Specificity is defined success rates for person
Diagnosed No Cancer as equation (3):

$$Sensitivity\ (\%) = \frac{TN}{FP+TN} * 100 \tag{3}$$

5. CONCLUSION AND LIMITATION

Skin cancer is the most prevalent and fatal type of cancer. Melanoma is the most dangerous type of skin cancer and is curable when detected in its early stages. The detection of melanocytes in the epidermis is a crucial step in the diagnosis of melanoma. In this paper, the watershed segmentation method is used. Feature extraction is applied to the extracted segments. Shape and GLCM are the features that were retrieved. For categorization, the extracted characteristics are employed. SVM (Support Vector Machine) and Feed Forward Back Propagation are the classifiers (FFBP). Experimental results demonstrate the efficacy of the suggested approach, with an FFBP of 96% attained for picture segmentation and an accuracy of 98% created by the SVM classifier. The conclusion of this study is helping people with skin cancer undergo a CT scan. The scan is tested using a computer trained to analyze CT scan data. This method has been shown to reduce the time it takes to diagnose and minimize brain damage. Artificial intelligence in skin cancer detection has led to the creation of low-cost tests that can be widely used to detect and treat skin cancer early, thus preventing the condition from getting worse and possibly fatal.

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