International Journal of Mathematics and
Computer Science, **16**(2021), no. 4, 1783–1789

Detecting Skin Cancer Disease Using Multi Intelligent Techniques

Ansam Nazar Younis, Fawziya Mahmood Ramo

Department of Computer Science
University of Mosul
Mosul, Iraq

email: anyma8@uomosul.edu.iq, fawziyaramo@uomosul.edu.iq

(Received May 7, 2021, Accepted June 15, 2021)

Abstract

In this paper, we propose a new approach for classifying malignant moles. From each image, we extract ten different types of features. All attributes are inserted into multi intelligent techniques that give a very high rating among them.

1 Introduction

Skin diseases and tumors are difficult and complex diseases that may require a long treatment, given that they are properly diagnosed. Cancer, in particular, has caused more than 8.2 million deaths so far and it affects more than 14.1 million people worldwide [1]. In 2018, Mendes and da Silva [1] used CNN for Clinical Images. In 2019, Mohamed et al. [2] gave a learning technique using a convolutionary neural network solution with multiple configurations. In 2020, Trstenjak and Hrncic [3] proposed a mobile application depending on embedded CNN. The objective of our research is to select the most prominent features and extract the important characteristics from the medical images of skin cancer to pass those features to multi intelligent techniques for supervisor machine learning in order to classify the tumor as either malignant or benign.

Key words and phrases: Weighted $K-$Nearest Neighbor, Features Selection, Features Extraction, Malignant Moles, Benign Moles.
AMS (MOS) Subject Classifications: 68-xx.
ISSN 1814-0432, 2021, http://ijmcs.future-in-tech.net

2 Feature Selection and Extraction

A set of features was selected for extracting from skin cancer images:
1) Entropy: Shannon's definition of entropy was given in [4]:

$$e(i,j) = -\sum_{i}^{n}\sum_{j}^{m} log(p(i,j)), \tag{2.1}$$

where e is the entropy value of gray scale image matrix of size$(n * m)$, p denotes the pixel of the gray scale image, and (i,j) represents the position of the pixel.
2) Entropy filter: Uses of highlighting the borders of the forged areas. Assume that x is a pixel in the image "IM" and let R be the size of its rectangular neighborhood $(2*m+1)*(2*n+1)$. Construct a neighborhood histogram of R to measure the probability of each pixel in R. The pixel count in$R$ will be:

$$R_x = 4*m*n + 2(m+n) + 1. \tag{2.2}$$

For each pixel, $q_i \in R$ is denoted by P_i and n_i is the number of pixels with the same intensity as that of the pixel, and for each point x, the probability is given by :

$$P_i = n_i/R_x. \tag{2.3}$$

3) Local Standard Deviation (LSD): This filter is the result of calculating the standard deviation of the neighbors of the pixels with a window size of $3*3$. As for the pixels on the edges, a symmetrical padding is done [5].
4) Range filter: Each value results from the value of the range VR which is the maximum value - the smallest value of the points that are neighbors with a window area of $3*3$ around the corresponding point in the input image [6].
5) Histogram equalization: It increases the range of color contrast in digital images, converting the image into an image with moderate graphics and uniform distribution of the image's colors approximately [7].
6) Shape (Horizontal projection): This can be calculated by finding the sum of the pixel values in horizontal lines (rows) [8].
7) Shape (Vertical projection): This can be calculated by finding the sum of the pixel values in the vertical lines (columns) [8].
8) Calculate the area of black points: To count the number of dark spots (pixels), we must follow a set of steps to avoid possible errors:
• First, the image is converted from gray to binary color (black and white), with threshold 0.6.
• Secondly, close the holes in the black spots by "morphological" closing [7]

on the binary image using single structure element 4.
• Thirdly, make sure that there is no black frame for the image.
• Finally, the number of black pixels is calculated freely, as the number of points increases, the more warning there is a danger.
9) Find the number of darker areas: Using Label Connected Components with 8−connected objects found for Gestalt Theory of perception [9].
10) Principal Component Analysis (PCA): After obtaining the components and characteristics of each image, these numbers are processed by using the following equations:

$$s = Mean(Mean(coefficient)) \tag{2.4}$$

$$b = \frac{s}{(_{10}floor(log_{10}(s)))} \tag{2.5}$$

$$feature = abs(b), \tag{2.6}$$

where s is the coefficient matrix of PCA algorithm

3 Multi Intelligent Techniques

3.1 Weighted KNN Classifier (W-KNN)

One of the most famous supervised learning algorithms in pattern classification is the $K-$nearest Neighbor rule (KNN) since it was first implemented. Given an unknown sample t, KNNs of the m training samples the count number of k_i samples belonging to class c_i. However, KNN has to find t closest vectors for the designing sets using the Euclidean distance (D) between $t^{'}$: a training vector and t^{NN} [10]:

$$D(t^{'}, t^{NN}) = \sqrt{(t_1^{'} - t_1^{NN})^2 + (t_2^{'} - t_2^{NN})^2} \tag{3.7}$$

w_i is the weight for i nearest neighbor for $t^{'}$ category. Then

$$w_i^{'} = \begin{cases} \frac{(D(t^{'},t_k^{NN}) - D(t^{'},t_i^{NN}))}{(D(t^{'},t_k^{NN}) - D(t^{'},t_1^{NN}))} & \text{if } D(t^{'}, t_k^{NN}) \neq D(t^{'}, t_1^{NN}) \\ 1 & \text{Otherwise} \end{cases} \tag{3.8}$$

3.2 Quadratic SVM (QSVM)

The Support Vector Machines algorithm was first introduced to classify and obtain estimate solutions for nonlinear tasks and its performance h relies on quadratic programming for optimization and structural risk reduction theories within statistical learning over many other traditional machine learning algorithms [11].

3.3 Boosted Trees Ensemble (BTE)

BTE is a method that can generate a variety of many classifiers by performing manipulations on a training dataset that is given to the basic learning algorithm. Even though boosted trees are more resistant to deception than neural networks, they can be effectively tackled by including new evading instances in the training dataset during boosting [12].

3.4 Linear SVM (LSVM)

LSVM is a useful technique to deal with high-dimensional details. Although its test set accuracy is comparable to that of a non-linear SVM, the problem formulations, its solvers, and optimization techniques to make the solvers more effective are all part of the linear SVM method [13].

3.5 Medium KNN (M-KNN)

The samples are sorted into groups based on their k closest neighbors. For distinction, Medium KNN uses more neighbors than Fine KNN. The algorithm will have a low differentiation function as a result of this kind [14].

4 Results and Discussion

To achieve the desired results, 2000 images of skin cancer (benign and malignant) were allocated for the training process. Also, a set of images were allocated for the testing process that included 360 images of benign moles and 295 of malignant ones. The proposed algorithm for using Weight KNN as a supervisor machine learning was implemented in two stages: a training stage and a testing stage. The results obtained after implementing the

Table 1: Results for testing some of the intelligence techniques used to classify skin cancer compared with the results of the proposed technique

Alg.	Type	AR	T-Classes	F-Classes	Total Of Image	TPR	FNR	PPR	FDR
QSVM	B	78.6	297	63	360	83	18	79	21
QSVM	M	78.6	218	77	295	74	26	78	22
BTE	B	85.6	326	34	360	91	9	84	16
BTE	M	85.6	235	60	295	80	20	87	13
LSVM	B	73	299	61	360	83	17	72	28
LSVM	B	73	116	179	295	61	39	75	25
M-KNN	B	74.7	298	62	360	83	17	74	26
M-KNN	M	74.7	191	104	295	65	35	75	25
W-KNN	B	100	360	0	360	100	0	100	0
W-KNN	M	100	295	0	295	100	0	100	0

proposed algorithm for classification between benign and malignant skin cancer pictures to compare them with a set of other algorithms using a set of measures [15].

4.1 Training and Testing Stages

We note that the result of training the proposed technique on the first 1000 images of the 2000 total different images of skin cancer was about 99.9 percent for benign (B) skin cancer images and about 100 percent for malignant melanoma images (M) in the classification. After all, the benign images are more difficult to classify because the injury may be large or multiple in the same area with cuts emerging outside the normal skin. For the next 1000 images, we noticed that the result of training was about 100 percent. The proposed Weight KNN algorithm was implemented to classify many various skin cancer images, numbering 360 benign skin cancer images and 295 malignant images and the results were excellent as well. In this table, we find that the results were complete, which indicates the response of the machine to the technique used to classify the images (Accepted Rate:AR) gave the desired improvement in achieving that goal. The examination phase was implemented on a number of different intelligent algorithms and techniques and for the same sample of images; namely, Quadratic SVM, Boosted Trees Ensemble, Linear SVM, Medium KNN. The results of the proposed algorithm using the Proposed Weight KNN in the machine learning were compared with them in the examination phase, as shown in table 1

5 Conclusion

From the results, it became clear to us that the use of the W-KNN algorithm as an intelligent technique in supervised machine learning is a very powerful technique in classifying skin cancer and making sure that this color change in the skin or the appearance of some skin growths, whether they are benign or malignant, which may contribute in saving lives, especially when the clinical diagnosis is difficult in some complex cases that may not appear directly to the naked eye. In addition, obtaining a classification ratio of close to 100 means that the technique is reliable.
For future research, the algorithm may be developed to classify and identify other skin diseases such as allergies of all kinds, congenital defects, after the availability of sufficient images for each disease and the addition of data of another type to help in the rapid diagnosis and development to be an expert system for Dermatology.

References

[1] Danilo Barros Mendes, Nilton Correia da Silva, Skin lesions classification using convolutional neural networks in clinical images, arXiv preprint arXiv:1812.02316,2018.

[2] Abeer Mohamed, Wael A. Mohamed, Abdel Halim Zekry, Deep learning can improve early skin cancer detection, International Journal of Electronics and Telecommunications, **65,** (2019).

[3] Bruno Trstenjak, Marko Hrncic, MOBILE Application for Skin Cancer Risk Prediction Based on Embedded Convolution Neural Network Model, Annals of DAAAM & Proceedings, **7,** no. 1, (2020).

[4] Mihran Tuceryan, Anil K. Jain, Texture Analysis, Handbook of pattern recognition and computer vision, World Scientific, (1993), 235–276.

[5] Norhashimah Mohd Saad, N. Nabilah, S. Abdul, Shape Defect Detection using Local Standard Deviation and Rule-Based Classifier for Bottle Quality Inspection, Indones. J. Electr. Eng. Comput. Sci., **8,** no. 1, (2017), 107–114.

[6] Firas Ajil Jassim, Image denoising using interquartile range filter with local averaging, arXiv preprint arXiv:1302.1007, 2013.

[7] Muna Jaffer Al-Shamdeen, Ansam Nazar Younis, Hiba Adreese Younis, Metaheuristic algorithm for Capital Letters Images Recognition, Computer Science, **16,** no. 2, (2020), 577–588.

[8] Mehmet Türkan, Montse Pardas, A. Enis Cetin, Human eye localization using edge projections, Proceedings of the 2nd International Conference on Computer Vision Theory and Applications, Institute for Systems and Technologies of Information, Control and Communication,(2007), 410–415.

[9] Costantino Grana, Daniele Borghesani, Rita Cucchiara, Optimized block-based connected components labeling with decision trees, IEEE Transactions on Image Processing, **19,** no. 6, (2010), 1596–1609.

[10] Ivan Dokmanic, Reza Parhizkar, Juri Ranieri, Martin Vetterli, Euclidean distance matrices: essential theory, algorithms, and applications, IEEE Signal Processing Magazine, **32,** no. 6, (2015), 12–30.

[11] Mingqing Hu, Yiqiang Chen, James Tin-Yau Kwok, Building sparse multiple-kernel SVM classifiers, IEEE Transactions on Neural Networks, **20,** no. 5, (2009), 827–839.

[12] Alex Kantchelian, J. Doug Tygar, Anthony Joseph, Evasion and hardening of tree ensemble classifiers, International Conference on Machine Learning, PMLR, (2016), 2387–2396.

[13] Vinod Kumar Chauhan, Kalpana Dahiya, Anuj Sharma, Problem formulations and solvers in linear SVM: a review, Artificial Intelligence Review, **52,** no. 2, (2019), 803–855.

[14] Ameer Ali, Mohammed Alrubei, Laith Falah Mohammed Hassan, Mohannad Al-Ja'afari, Saif H. Abdulwahed, Diabetes Diagnosis Based on KNN, IIUM Engineering Journal, **21,** no. 1, (2020), 175–181.

[15] Dhafar S. Hammadi, Ansam N. Younis, Fawzia M. Ramo, Hybridization and Modification of the PSO Algorithm and Its USE in Personal Recognition by OPG X-Ray, Journal of Engineering Science and Technology, **16,** no. 1, (2021), 325–338.