# Extreme Learning Machine for Melanoma Classification

Sajidah Al-Hammouri *, Malak Fora*, Mohammed Ibbini*

*Biomedical Engineering Department, Jordan University of Science and Technology

Irbid, Jordan

Emails: sfalhammouri18@eng.just.edu.jo, mafora18@eng.just.edu.jo, mohib@just.edu.jo

2021 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT) | 978-1-6654-4293-0/21/$31.00 ©2021 IEEE | DOI: 10.1109/JEEIT53412.2021.9634135

*Abstract*— **Melanoma is considered the most dangerous type of skin cancer worldwide. Early detection of this cancer type plays an important role in the treatment process. Many invasive methods such as shaving were used for taking a biopsy from the patients for diagnosis. However, nowadays image processing techniques combined with machine learning can play a significant role in the diagnosis of medical images in a non-invasive way. To this end, this study aims to use machine learning algorithms for the early diagnosis and treatment of this type of cancer. Methodologically, the steps involved in this study are pre-processing of melanoma images, segmentation, features extraction, and then classification using the extreme learning machine (ELM) classifier. To the best of our knowledge, this classifier has not been used before for such types of images. This study aims to test the efficacy of using ELM in classifying these types of images compared with other common types of Machine learning algorithms such as Random Forest, support vector machine (SVM), and K-nearest neighbor (KNN). Promising results were obtained from ELM with an accuracy of 97%, 91% using 11 features, and 5 features, respectively.**

*Keywords*— **Melanoma, Features Extraction, Classification, Extreme Learning Machine (ELM), SVM, KNN**

## I. INTRODUCTION

Human body skin is composed of three main layers epidermis, dermis, and subcutaneous tissue (hypodermis). The epidermis is the outermost layer of human skin which helps to protect our body against ultraviolet light. This layer has three components, namely; squamous cells, basal cells, and melanocytes, which are located at the deepest part of the epidermis as shown in fig 1. These cells produce melanin, which is responsible for skin color and absorbing harmful light to prevent them from going deeply towards the deepest layers [1]. Melanoma is a type of skin cancer that is considered the most common type among other human cancers and usually developed when melanocytes start to grow out of control and in an abnormal way after being exposed to ultraviolet radiation from the sun which damages the DNA inside cells of the skin [2]. It is more common among the white faired-skinned population in Europe, North America, and Australia, whereas people with dark skin are less affected [3].

Over the past few decades, the rates of melanoma have been rising rapidly, with 75% of deaths make it the deadliest form of skin cancer [4]. According to the American cancer society, 100,350 new cases of melanoma will be diagnosed, and 6850 people will die because of melanoma in 2020 [5]. Thus, the detection of melanoma in its early stages is crucial and increases the chances of cure.

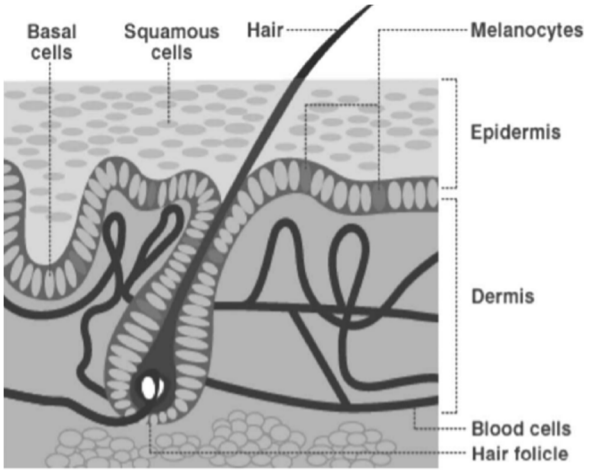


Fig. 1 Skin layers [1]

Firstly, diagnosing skin cancer can be conducted by visual inspection where the physician may look at the inspected region to determine whether it is normal or not. Then further invasive lab testing may be needed to confirm that diagnosis by using a thin, sharp blade to take a shaving biopsy of the suspected region. However, this diagnostic technique which depends on the naked eye is not accurate. Furthermore, the diagnostic performance was increased when the dermoscopy was developed which is a non-invasive medical imaging technique used to take a magnified image for melanoma. However, the manual inspection made by dermatologists is still a time-consuming process, even well-trained dermatologists may give different diagnostic results [6]. In the last few years, the demand for using machine learning has been increased rapidly especially for data mining segmentation and classification problems. In this regard, computer aid diagnostic systems (CAD) for automated recognition are highly demanded, in which a non-invasive technique has greatly enhanced the interpretation of medical images for the Physician and

contributed to early diagnosis of the disease. Furthermore, it can also give economic benefits to hospitals.

This paper introduces an algorithm to extract and classify dermoscopic images into two categories (normal and abnormal) using different classifiers, including Extreme machine learning (ELM) classifier. To the best of the author's knowledge, this is the first time that this classifier has been used to classify such types of images. Where it is characterized by its speed, flexibility, simplicity, as well as its low training error rate. The remaining of this paper is divided as follows: section III for the materials and methods section, section IV for results and discussion and finally section V for conclusion and future work.

## II. RELATED WORK

Doukas et al. developed a system to detect the moles in skin images using a mobile application and classify them as melanoma, nevus, and benign lesions. The result showed that the Support Vector Machine (SVM) has an accuracy of 77.06% [7]. In [8], the images of the skin were pre-processed and different classifiers such as support vector machine, decision trees, K-nearest neighbor, and ensemble classifiers were used for classifying moles pictures to benign and melanoma using GLCM, wavelet, and a textural feature(Trauma). Achieving accuracies 100%, 87.5%, 75%, and 87.5% using SVM, KNN, Ensemble, and Decision tree, respectively.

Jaleel and Salim used the Maximum Entropy Threshold to segment the pre-processed images, followed by feature extraction using the Grey Level Co-occurrence Matrix(GLCM) and Artificial Neural Network (ANN) for the c1assification of the data set into normal or abnormal with 88% accuracy [9]. While in [2], the authors used the Mean Shift algorithm for segmentation. After extraction of ABCD features, they apply the RELIEF algorithm for feature selection and Principle component analysis for dimension reduction, three classifiers were used: Decision Tree, KNN, and SVM classifier, which showed superiority in the performance over the two classifiers with 78.2% accuracy.

Parmar et al. used the YCbCr color space method for segmentation to extract color, shape, and texture Haralic 13 features, and then the images were classified using three types of classifiers: support vector machine, artificial neural network, and random forest with 87.05%, 75%, 90%, respectively [10].

A study conducted in [11] used Adaptive Thresholding for segmentation and found that the combination between extracted color and texture features from 150 dermoscopic images gives better results for SVM classification with 93% accuracy. While SVM classifier in [12] had an accuracy of 92.1% after using PCA for texture, ABCD, and statistical extracted features. Alasadi and Alsafy extracted color, texture, and geometry features from 200 RGB images for malignant melanoma and achieved 93.9% accuracy using the ANN classifier [13].

An efficient algorithm to predict melanoma was proposed in [14]. In this study, fifteen Statistical and Shape features were extracted from Otsu's segmented images entered into different classification techniques like ANN, Adaptive neuro-fuzzy inference system (ANFIS), SVM, Deep learning-based neural networks (DLNN), Real AdaBoost, Modest AdaBoost, GentleAdaBoost, Hybrid AdaBoost with accuracies 90.12%, 90.39%, 90.44%, 92.89%, 86.52%, 86.84%, 89.91, and 91.73% respectively. Also, a Convolution Neural Network (CNN) is used to extract features from 337 images to train an SVM classifier. The experimental results show that the accuracy of the system is 94.1% [15]. Moreover, a Radial Basis Function Network(RBFN) and SVM resulting in 87%, and 91% respectively for images, in which geometry, GLCM, and color features were extracted [16].

Achakanall and Sadashivappa used processed images to extract statistical and medical features such as ABCD parameters, followed by Artificial Neural Networks for the classification of Malignant Melanoma from non-cancerous with an accuracy of 92% [17].

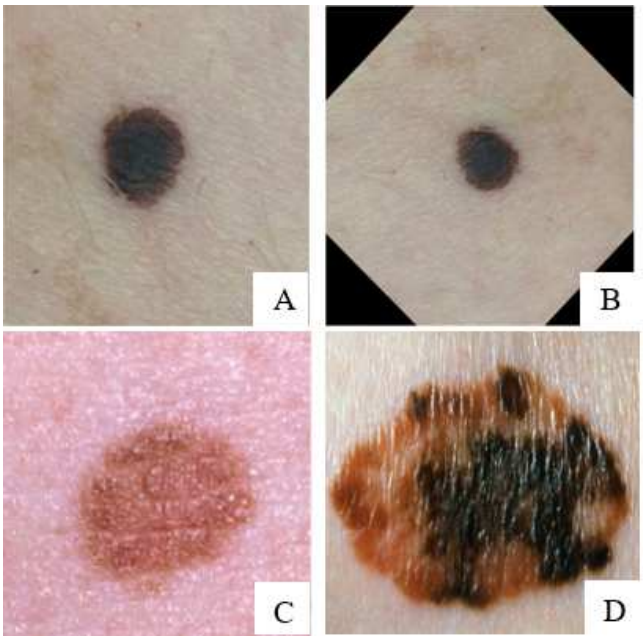


Fig. 2 Example of the augmented image. A: Original Image, B: Rotated Image, C: Normal mole [19], D: Melanoma [20].

## III. MATERIALS AND METHODS

### A. Dataset Description

The dataset was generated by collecting labeled images (Normal, /Melanoma) from the dermatology database used in MED-NODE [18] and from different websites [19], [20]. In which these websites are specialized for melanoma skin cancer. Moreover, all of these images were captured in JPEG format.

To increase the number of normal images in our dataset to have an equally sized dataset, different augmentation techniques were used such as reflection, rotation, and translation over X and Y. Fig. 2 below shows an example of a rotated image where A is the image before the rotation and B is the rotated image. So, the total number of images after augmentation is 200 RGB images with 100 images for each class (Normal/Melanoma) which are shown in Fig 2.

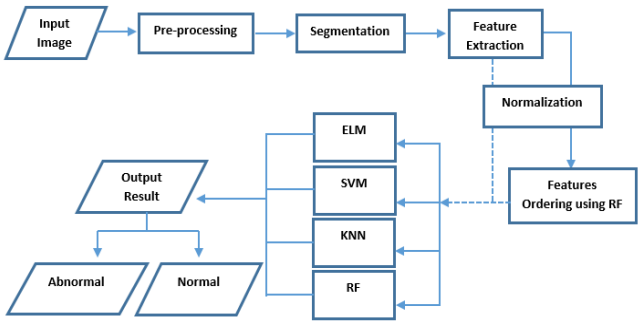


Fig. 3 Block diagram for the proposed method

Fig. 3 shows a block diagram for the proposed method. The following subsections give more explanation for each stage.

*B. Image Pre-processing*

Pre-processing is an important step to strengthen some of the important features of the image and removing the noise and unwanted distortions before the feature extraction step. All the images were resized to 512 x 512 pixels as the first step in the pre-processing phase [9]. Followed by various techniques for enhancing the converted grey level images obtained such as enhancing the Contrast and Histogram equalization to make the image contrast better, thus more accurate separation for the region of interest (ROI) [21].

For noise filtering, a 3x3 sliding window was used to remove noise and unwanted information. One of the various techniques of filters is the median filter [9], which have been used here in this work to make the skin cancer image smoother and reduce the impact of noise before the classification process starts while keeping the edges. Where this step, as well as the following step (segmentation), were based on Alquran et al work [12].

*C. Segmentation*

Extracting the lesion region is considered one of the most important steps after the pre-processing stage. Different methods could be used for segmentation, however, we use Otsu thresholding as it is considered one of the most important techniques to extract the lesion area which is an automatic threshold-based selection region method depends on the histogram of each used grey image. This process is followed by filing and morphological opening techniques with a disk-shaped structuring element with a radius of 10 pixels to eliminate small unwanted pixels and to ensure that the separated region is more obvious.

*D. Feature Extraction and Normalization*

After the region of interest is being obtained from the segmentation process, different features were extracted such as Texture, Statistical, and Dermoscopic features(ABCD) [12]. The grey-Level Co-Occurrence Matrix (GLCM) is used to study texture features such as contrast, correlation, energy, and homogeneity. Where (ABCD) stands for Asymmetry, Border irregularity, Color changes, and Diameter with a value greater than 1/4 inch (about 6 millimeters) for melanoma [22-25]. Those features are considered an important guide to distinguish skin lesions from others, where the American Academy of Dermatology always advises looking at these features as the first step in the examination. Statistical features could also play an important role in distinguishing melanoma images from normal ones such as Mean, Standard deviation, skewness, and kurtosis.

In total eleven features were extracted after combining the four Dermoscopic features in one variable called Total Dermoscopy Score (TDS) of the dermoscopic images and it is calculated after the extraction of four medical features ABCD [24]. TDS is given by:

$$TDS = A*1.3 + B*0.1 + C*0.5 + D*0.5 \quad (1)$$

All the extracted features were normalized using Z-score normalization (Z) to eliminate the effect of outlier values using the following equation [25]:

$$Z = \frac{V - \mu}{\sigma} \quad (2)$$

Where V is the value of the extracted features, μ is the mean value of the feature and σ is the standard deviation of the feature. The value will be normalized to zero if it is equal to the mean of all the values of the feature. If it is above the mean it will be a positive number, otherwise, it will be a negative number.

*E. Classification Algorithms*

***Extreme learning machine***: It is a feedforward neural network that consists of three main layers; input, hidden (single or multi-layer of hidden nodes), and output layers. Fig. 4 demonstrates the basic structure of ELM where ω represents connected weights between input and hidden layers. β is the weight between the hidden layer and output layer. There are a lot of characteristics for ELM that motivated us to use it here in our work, first of all, it is a new simple learning algorithm; in which, it can give a good performance at a very fast learning speed because the weights that connect inputs to hidden nodes are chosen randomly and remain constant during training/predicting phases. On the other side, the weights between hidden nodes and outputs can be calculated and trained very fast [26]. This feature gives ELM superiority over the backpropagation algorithms to overcome overfitting and the slow training speed because ELM parameters are tuned only one time. Whereas weights of conventional neural networks need to be tuned iteratively. Many studies showed that ELM was faster than SVM with good predictive performance [27], [28]. In our work, we used ELM with the radial basis function kernel (ELM-RBF).

***Support Vector Machine (SVM):*** it is a supervised machine learning algorithm that was found by Boser, Guyon, and Vapnik in 1992 [29]. Its principle depends on finding the best hyperplane that separates data set into different classes. Choosing the best hyperplane depends on the one that maximizes the margin or distance between two classes [30]. Here in our work to make data separable We used SVM with a mapping technique called Gaussian radial basis function (RBF).

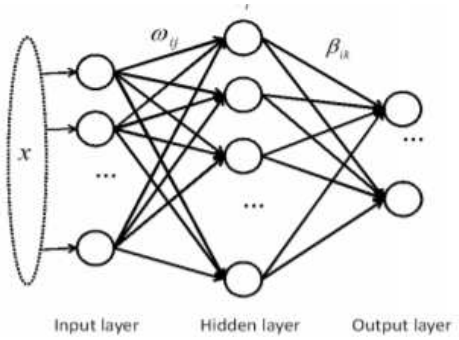


Fig. 4 Basic structure of ELM [26]

***K-nearest neighbor (KNN):*** it is a supervised machine learning, it could be used for data classification and regression. It is based on clustering data into some subsets (clusters) equal to the number of classes. Classifying observations are obtained concerning the nearest neighbor points related to the observation. Determining the optimal value of the K number helps in overcoming underfitting and overfitting problems as a result of choosing large, small K-values, respectively. In this work, the optimal K value was determined using the Calinski-Harabasz technique. And as shown in Fig.5 it was found that the optimal K-value was 5.

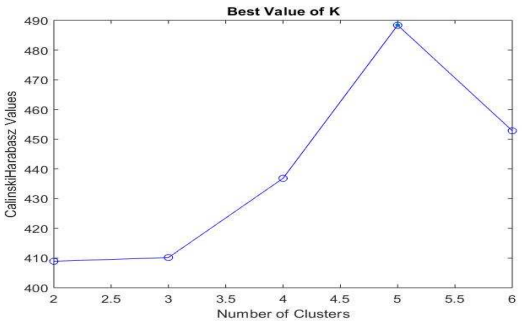


Fig.5 Determining the optimal K value using the Calinski-Harabasz method

***Random forest classifier (RF)****:* consists of many decision trees. It is used in classification and regression-based problems. Prediction or classification results are obtained by the voting principle between individual trees. Herein, the number of trees was set to 100.

In addition to classification, RF was also used to figure out the most 5 significant features that play an important role in the classification process, where they were ordered according to their relative importance in making decisions. Just as shown in fig.6. The five features were energy, TDS, entropy, skewness, and circulation.

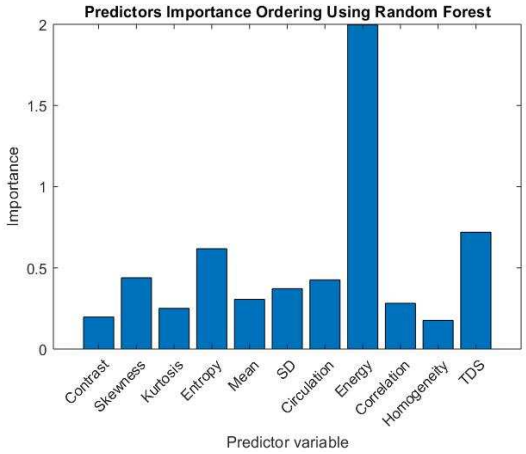


Fig. 6 Arrange features in order of importance using R-F

## IV. RESULTS AND DISCUSSION

Fig (7-14) show the confusion matrices for the used classifiers. Accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) measurements were used to evaluate the performance of models. Using confusion matrix, statistical indices are calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (4)$$

$$Specificity = \frac{TN}{TN+FP} \quad (5)$$

$$PPV = \frac{TP}{TP+FP} \quad (6)$$

$$NPV = \frac{TN}{TN+FN} \quad (7)$$

Where TP, TN, FP, FN stand for true positive, true negative, false positive, and false negative, respectively.

The images were divided into 70% training and 30% testing, where all the classifiers received the same training and testing datasets. In addition, K-fold cross-validation was used to prevent overfitting problems with k-fold number =5. The accuracy of each classifier is shown in tables 1 and 2. The results of ELM, KNN, RF, SVM with 11 features are 97%, 94%, 97%, and 94%, respectively. While the recorded accuracies using 5 features are 91%, 91%, 95.5%, and 94% respectively. So the results show that the accuracies of the used classifiers decreased with 5 features except for SVM which maintains the same accuracy with a value of 94% in both cases. Table 3 shows relatively high statistical parameters of ELM for 11

features compared with 5 features. In this study, the SVM with only 5 features achieved 94% testing accuracy outperforming many results in the literature [2][10-12], in which they achieved 78.2%,87.05%, 93%, and 92.1, respectively. Also, KNN with the same selected features showed good performance (91%) in comparison with 76.4 % and 87.5% in [2]. Whereas RF achieved 95.5% testing accuracy outperforming results obtained in [10] where they achieved 90% testing accuracy. The highest results were obtained by ELM and the Random forest with accuracy reaches 97% with 11 features. However, the running time for ELM was 0.011 seconds while for Random forest 1.33 seconds, which means that ELM is 120 times faster than RF. Also, the results show that the ability of ELM to distinguish between normal and abnormal moles is relatively high compared to the others. Further improvements could be done for enhancing the performance of this classifier.

## V. Conclusion and Future Work

Early detection of skin cancer plays an important role in the recovery process. The proposed algorithm in this work which starts with image preprocessing and ending up with ELM classification shows promising results for diagnosing melanoma skin cancer. Also, using the ELM for the first time is very effective and shows comparable results to the different classifiers found in the literature with accuracy reach 97% for 11 features and 91.04% for 5 features. However, the running time for the ELM was lower than the random forest which means ELM is less complex, faster, and less computational time is needed for its training process. By taking the benefit from the ELM classifier, classification can be applied in real-time and for mobile phone applications in a much more efficient way with high accuracy and least user intervention.

In the future, we hope to do further improvements by using larger datasets with multiclass problems to be able to implement this algorithm in a mobile application or in any home monitoring device to help patients making their diagnoses without the need for going to the hospital.

TABLE1. Classification results for all classifiers using 11 features.

| Classifier | ELM | KNN | R-F | SVM |
|---|---|---|---|---|
| Accuracy | 97% | 94% | 97% | 94% |

TABLE 2. Classification results for all classifiers using the top 5 features.

| Classifier | ELM | KNN | R-F | SVM |
|---|---|---|---|---|
| Accuracy | 91% | 91% | 95.5% | 94% |

TABLE3. STATISTICAL PERFORMANCE FOR ELM ON 11 AND 5 FEATURES

| ELM | Sensitivity | Specificity | PPV | NPV |
|---|---|---|---|---|
| 11 features | 93.9% | 100% | 100% | 94.4% |
| 5 features | 90.9% | 91.2% | 90.9% | 91.2% |


Fig. 7 ELM with 11 features

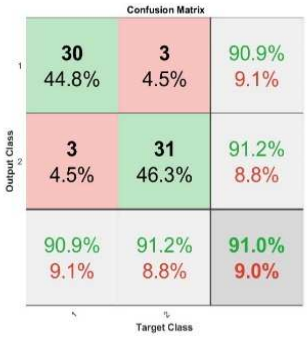


Fig.8 ELM with 5 features


Fig.9 KNN with 11 features

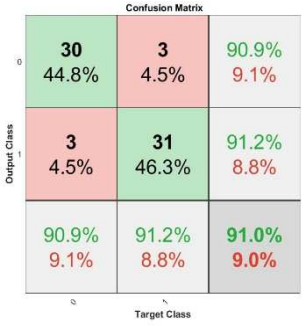


Fig. 10 KNN with 5 features


Fig. 11 RF with 11 features

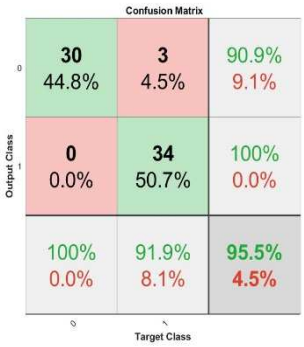


Fig. 12 RF with 5 features

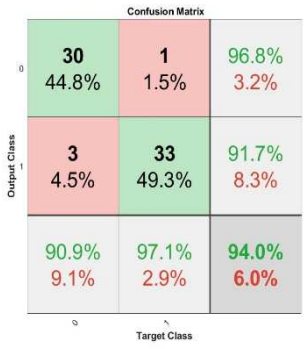


Fig. 13 SVM with 11 features


Fig. 14 SVM with 5 features

## REFERENCES


[1] I. Maglogiannis, C. N. Doukas, and S. Member, "Overview of Advanced Computer Vision Systems for Skin Lesions Characterization," vol. 13, no. 5, pp. 721–733, 2009.

[2] N. C. Lynn and Z. M. Kyu, "Segmentation and Classification of Skin Cancer Melanoma from Skin Lesion Images," pp. 0–5, 2017.

[3] C. Karimkhani *et al.*, "The global burden of melanoma: results from the Global Burden of Disease Study 2015," *Br. J. Dermatol.*, vol. 177, no. 1, pp. 134–140, 2017.

[4] L. Yu, H. Chen, Q. Dou, J. Qin, and P. A. Heng, "Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks," IEEE Trans. Med. Imaging, vol. 36, no. 4, pp. 994–1004, 2017.

[5] "Melanoma Skin Cancer Statistics." [Online]. Available: https://www.cancer.org/cancer/melanoma-skin-cancer/about/key-statistics.html.

[6] M. Binder et al., "Epiluminescence microscopy. A useful tool for the diagnosis of pigmented skin lesions for formally trained dermatologists.," 2015.

[7] C. Doukas, P. Stagkopoulos, and C. T. Kiranoudis, "Automated Skin Lesion Assessment using Mobile Technologies and Cloud Platforms," no. c, pp. 2444–2447, 2012.

[8] N. Raut, A. Shah, S. Vira, and H. Sampat, "A Study on Different Techniques for Skin Cancer Detection," pp. 613–617, 2018.

[9] J. A. Jaleel and S. Salim, "Computer Aided Detection 01 Skin Cancer," pp. 1137–1142, 2013.

[10] B. Parmar, "Automated Melanoma Types and Stages Classification for dermoscopy images," pp. 1–7, 2019.

[11] J. C. Kavitha and A. Suruliandi, "Texture and color feature extraction for classification of melanoma using SVM," in 2016 International conference on computing technologies and intelligent data engineering (ICCTIDE'16), 2016.

[12] H. Alquran, I. A. Qasmieh, A. M. Alqudah, S. Alhammouri, and E. Alawneh, "The Melanoma Skin Cancer Detection and Classification using Support Vector Machine," 2017.

[13] A. H. H. Alasadi and B. M. Alsafy, "Diagnosis of Malignant Melanoma of Skin Cancer Types," no. January, 2017.

[14] J. Premaladha and K. S. Ravichandran, "Novel Approaches for Diagnosing Melanoma Skin Lesions Through Supervised and Deep Learning Algorithms," pp. 1–12, 2016.

[15] D. A. Shoieb, S. M. Youssef, and W. M. Aly, "Computer-Aided Model for Skin Diagnosis.Using Deep Learning," no. January 2017, 2016.

[16] R. Gaonkar, K. Singh, G. R. Prashanth, and V. Kuppili, "Lesion Analysis towards Melanoma Detection using Soft Computing," Clin. Epidemiol. Glob. Heal., 2019.

[17] Santosh Achakanalli andG Sadashivappa, "Skin cancer detection and diagnosis using image processing and Implementation using neural networks and ABCD parameters," Jun-2014. [Online].

[18] I. Giotis, N. Molders, S. Land, M. Biehl, M. F. Jonkman, and N. Petkov, "MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images," Expert Syst. Appl., vol. 42, no. 19, pp. 6578–6585, 2015.

[19] "Normal moles pictures library | Wide overview for comparison," 20-Jun-2017. [Online]. Available: https://www.skinvision.com/moles-pictures/.

[20] "Melanoma pictures | Example pictures of melanoma symptoms," 27Jun2017.[Online].Available:https://www.skinvision.com/melanoma/pictures/.

[21] P. S. B. Chitradevi, "An Overview on Image Processing Techniques | Semantic Scholar," 2014.

[22] H. Asha Gnana Priya, J. Anitha, and J. Poonima Jacinth, "Identification of Melanoma in Dermoscopy Images Using Image Processing Algorithms," 2018 Int. Conf. Control. Power, Commun. Comput. Technol. ICCPCCT 2018, pp. 553–557, 2018.

[23] M. Hossen Bhuiyan, I. Azad, and M. Uddin, "Image Processing for Skin Cancer Features Extraction," Int. J. Sci. Eng. Res., vol. 4, no. 2, pp. 1–6, 2013.

[24] G. Grammatikopoulos, "Automated malignant melanoma detection using MATLAB," Proc. 5th Int. Conf. Data …, no. October, pp. 91–94, 2006.

[25] H. Iyatomi et al., "An improved Internet-based melanoma screening system with dermatologist-like tumor area extraction algorithm," Comput. Med. Imaging Graph., vol. 32, no. 7, pp. 566–579, 2008.

[26] W. Cao, J. Gao, Z. Ming, and S. Cai, "Some Tricks in Parameter Selection for Extreme Learning Machine," IOP Conf. Ser. Mater. Sci. Eng., vol. 261, no. 1, 2017.

[27] L. Zhang, D. Zhang, and F. Tian, "SVM and ELM: Who Wins? Object Recognition with Deep Convolutional Features from ImageNet," pp. 249–263, 2016.

[28] R. Zhang, G. Bin Huang, N. Sundararajan, and P. Saratchandran, "Multicategory classification using an extreme learning machine for microarray gene expression cancer diagnosis," IEEE/ACM Trans. Comput. Biol. Bioinforma., vol. 4, no. 3, pp. 485–494, 2007.

[29] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A Training Algorithm for Optimal Margin Classifiers," *CiteSeer*, 1992.

[30] A. Ng, "CS229 Lecture notes Margins : SVM," Intell. Syst. their Appl. IEEE, vol. pt.1, no. x, pp. 1–25, 2012.

[31] A. Alqudah and A. M. Alqudah, "Sliding Window BFased Support Vector Machine System for Classification of Breast Cancer Using Histopathological Microscopic Images," IETE J. Res., vol. 0, no. 0, pp. 1–9, 2019.