Design Studies and Intelligence Engineering
L.C. Jain et al. (Eds.)

doi:10.3233/FAIA220712

Melanoma Classification Using Machine Learning Techniques

J. Jacinth Poornima[a], J. Anitha[a], Asha Priya Henry[a], D Jude Hemanth[a]
[a]Department of ECE, *Karunya Institute Technology and Sciences, Coimbatore, India*

Abstract. Melanoma is the most deadly form of cancer which is easily curable if detected at the earlier stage. The main objective of this paper is to classify the Melanoma and Non-melanoma using dermoscopy images from the Med Node Dataset. The images are enhanced by bottomhat filter, and then segmentation is done by two methods 1. Morphological Operations, 2. Otsu Thresholding. The features extracted from the segmented lesions are ABCD features, Statistical features and is given to the classifier. . The classification is done by Machine Learning Algorithms (FFNN, SVM, KNN). The performance is analysed by the sensitivity, specificity, accuracy, Positive predictive value, negative predictive value and manually by Total Dermatoscopy Score (TDS) for 9 different classification cases. The best among the cases is 96.7% accuracy is for FFNN algorithm.

Keywords. Melanoma, Segmentation, Machine Learning, Dermoscopy

1. Introduction

Malignant melanoma, often known as melanoma, is a highly aggressive form of skin cancer. Despite making up less than 7% of all cases of skin cancer, malignant melanoma accounts for cause up to 74% of all skin cancer-related fatalities. Each year Melanoma is increasing and more deaths due to the final stage of melanoma. 132,000 cases of melanoma skin cancer worldwide. The aberrant creation of melanin cells results in malignant melanoma. Performing local resection after an early diagnosis is currently the best course of action. If discovered early, a patient's 5-year survival rate can exceed 95%; if not, the likelihood of the malignant cells spreading to other body organs and tissues is high, and the patient's chance of survival is only slightly better than 50%. A microscope-based diagnostic technique called dermoscopy produces a magnified, illuminated image of the skin area, improving the clarity of the target area [1]. Fully Convolutional Residual Network (FCRN) employs a multi-scale contextual information integration technique to achieve accurate segmentation. Using produced prediction maps allows for more precise and reliable encoding of both global and local aspects of skin lesions. A very deep convolutional neural network can address a challenging medical picture problem [2]. Melanoma and non-melanoma skin cancers were classified in this research along with other two forms of skin cancer. A combination of both was employed to achieve greater outcomes than employing a color or gray image alone. K-means clustering, as opposed to the ABCD approach, is used for segmentation (Asymmetry, Boundary irregularity, color, Diameter). We used 170 dermoscopy photos in total, of which 75 were of melanoma and 75 were not. SVC and 1-NN achieved the maximum accuracy with the same number of feature sets when the performance of the four classifiers was evaluated

[3]. In a different method that was disclosed, the authors employed a wiener filter and an adaptive histogram equalization method for the pre-processing stage. They employed an active contour segmentation mechanism in their study. A sensitivity of 90%, accuracy of 95%, and specificity of 85% are observed for the SVM classifier used to classify the skin lesion into malignant or benign. The features employed in the system are extracted using GLCM. But for the experiments, they only used a limited dataset [4]. In another method it was developed a smart method for effective melanoma categorization and prediction. Image improvement techniques include the gaussian filter and Adaptive Histogram Equalization Equalization. Lesion and skin are segmented using a unique segmentation method called Normalized Otsu's Segmentation. It made the issue with changeable lighting less severe. Fifteen characteristics were retrieved from the segmented images and supplied into the suggested predictor (neural networks based on deep learning and hybrid AdaBoost SVM). The system's classification accuracy was 93% after being tested and validated using over 992 photos of benign and malignant tumors [5-7]. Changing the structure is a widely popular strategy in ensemble model creation. Individual feed-forward networks typically make up an ensemble of nets. The individual nets are often of the same network type, even though using so many, diverse types of networks is typically seen as fundamental to achieving the prediction performance of an ensemble. A fuzzy neural network (FNN) is an assessment solution that incorporates fuzzy logic with an artificial neural network, whereas a back propagation (BP) neural network is a type of multilayer forward network [8]. Both can handle ambiguous, nonlinear, and other poorly presented issues with ease. Here, we mix BP and FNN networks to form an ensemble model. Additionally, we create a meta-ensemble model, which consists of three ensembles with various network structures/types, to further optimize the effectiveness of the ensemble [11]. Another paper states The CNN techniques show that on the MED-NODE dataset, the identical Inception V3 CNN model only manages 0.82 ACC with 0.65 MCC. The PECK algorithm is created to enhance classification accuracy from sparse training data. It combines the Deep Ensemble Structure of Support Vector Machine and Random Forest classifiers with the Inception V3 CNN architecture. The ensemble outperforms the best earlier papers by a large margin, achieving 0.91 ACC and 0.83 MCC [9]. In advanced method like ConvLSTM, it takes the multi-level image features from the encoding model. But the scale-invariant features into the network to further improve performance by incorporating the derived features for each block of the decoding path [10]. For precise skin lesion segmentation, FCRN uses a multi-scale contextual information integration technique. The prediction is more accurate and reliable when generated prediction maps encode both global and local aspects of skin lesions [12-13]. Dermoscopy pictures were segmented, which was created to produce accurate result under challenging conditions. Dimensionality reduction employs PCA [14]. Even with the uneven distribution of images between classes, the suggested technique can accurately classify eight different types of lesions. To solve the issue of an imbalance in the number of photos between classes, performance improved when the number of images in all classes was reduced. When all architecture layers' weights were adjusted, we found that performance metrics improved more than when only the substituted layers were adjusted. Another model was put up to identify unknown photos using multi-class SVM and GoogleNet [15,16].

In this paper explains the proposed methodology which includes the dataset, image enhancement, image segmentation, feature extraction, classification and performance analysis. Section 3 gives the conclusion with comparison of 9 different cases in classification.

2. Proposed Methodology

2.1. Block Diagram

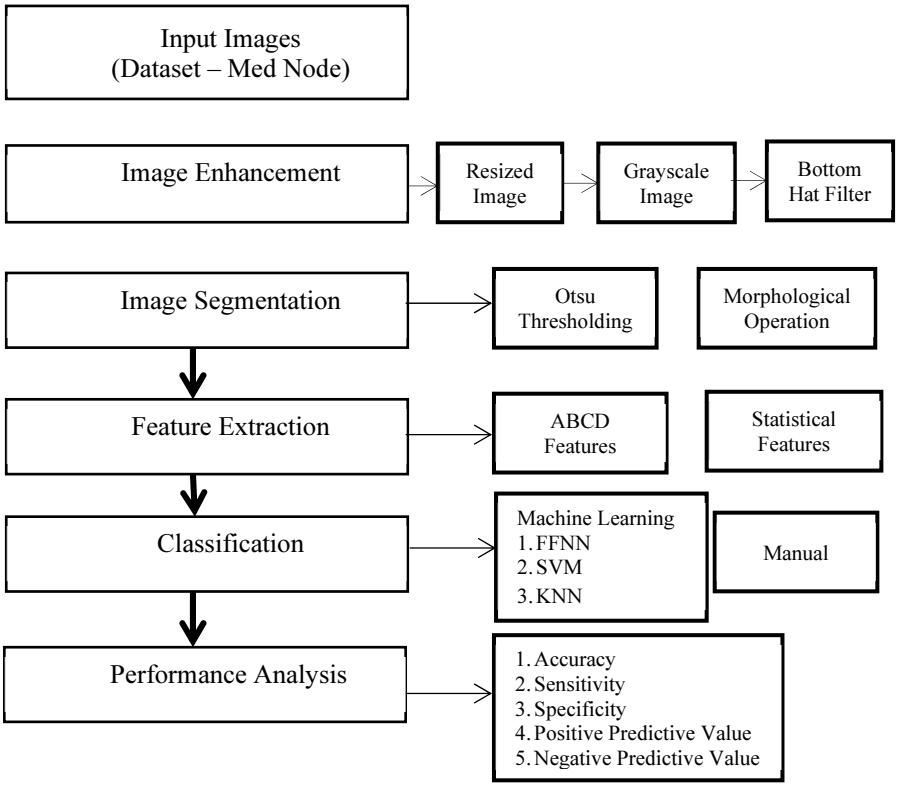


Fig:1 Proposed Block Diagram

Table 1. Framework of 9 classification cases

Case 1: Image Dataset-Bottom Hat Filter-Otsu Thresholding-ABCD Feature-Manual-Performance Analysis
Case 2: Image Dataset-Bottom Hat Filter-Morphological Operation-ABCD Feature-Performance Analysis
Case 3: Image Dataset-Bottom Hat Filter-Statistical Features-Machine Learning-Performance Analysis
Case 4: Image Dataset-Bottom Hat Filter-Otsu Thresholding-ABCD Feature-Machine Learning-Performance Analysis
Case 5: Image Dataset-Bottom Hat Filter-Morphological Operation-ABCD Feature-Machine Learning-Performance Analysis
Case 6: Image Dataset-Bottom Hat Filter-Otsu Thresholding-Statistical Feature-Machine Learning-Performance Analysis
Case 7: Image Dataset-Bottom Hat Filter-Morphological Operation-Statistical Feature-Machine Learning-Performance Analysis
Case 8: Image Dataset-Bottom Hat Filter-Otsu Thresholding-[ABCD + Statistical Feature]-Machine Learning-Performance Analysis
Case 9: Image Dataset-Bottom Hat Filter-Morphological Operation-[ABCD + Statistical Feature]-Machine Learning-Performance

2.2. Image Dataset

The input image is taken from the MedNode database. The MedNode dataset consists of 70 melanoma and 100 non-melanoma images from the digital archive images of the dermatology department at University Medical Centre Groningen (UMCG).

2.3. Image Enhancement

The image from the dataset is used for image enhancement and the flow is given in the figure 2.

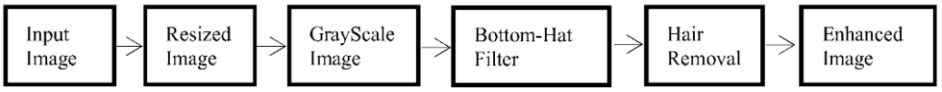


Fig:2 Block diagram of Bottom-Hat Filter

The input image is resized to 256*256 and is converted to grayscale image to speed-up the process. Bottom-Hat filter is applied for enhancing the hair in the skin dermoscopy image. The hair is removed by adding the input image with filtered image and the results are given in Figure 3. The Bottom-Hat filter function is given by

$$T_s(f) = f.s - f \quad \text{(Where, "s" is the structure element.)}$$

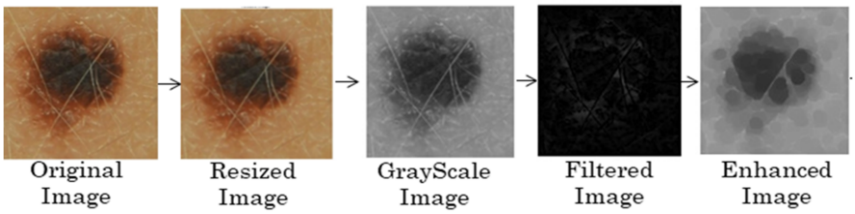


Fig:3 Results of Image Enhancement

2.4. Image Segmentation

The enhanced image output is taken as the input for the image segmentation process. There are two method's used for the segmentation of lesion.

2.4.1. Otsu's Method

Lesion segmentation from the enlarged picture is accomplished using the Otsu Thresholding method. T is the in-and-out estimated value, and the function of (x, y). T computes and establishes the two distinct regions. The new T value is then determined by averaging the two means. Iterations that are run repeatedly indicate minor differences in values that are completely different from the predefined parameter. The result of the Otsu Thresholding Method is shown in Fig 4.

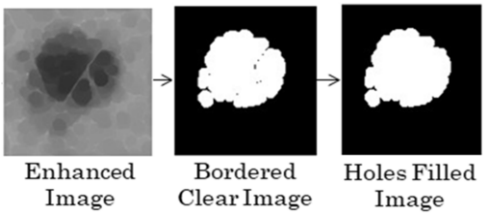


Fig:4 Stages of Image Segmentation by Otsu Threshold Method

2.4.2. Morphological Operation

The enhanced image is then turned into a binary image. If any associated components smaller than 30 pixels in size are removed, fill in any holes left in the binary image. To maintain the object's circular shape, add a structuring element with a disk form. In order to join the circles together to form an image, the spaces between the circles are filled and their edges are rounded off. Images that emphasize edges are produced using a binary mask and the Sobel filter. After the morphological dilation and erosion procedures, the final mask is created. In order to fill the image region, morphological operations are employed to eliminate the lighter pixels and suppress the bright structures. The result of the Morphological Image segmentation method is from the original image to the final image is shown below.

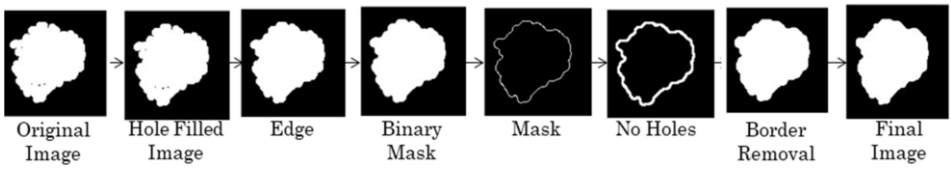


Fig:5 Stages of Image Segmentation by Morphological Method

2.5 Feature Extraction

The feature extraction is the process of analysing the parameters that represents the characters of the given input dataset. The parameters that are to be found are Area (A), Perimeter (P) is to find the number of edge pixels, Greatest and Shortest Diameter (GD, SD) which is the length of the line passing through the lesion blob centre and connecting two nearest points. The ABCD rule is used for calculate the Asymmetry lesion of the melanoma, Border Irregularity to detect the cancerous edges which ranges from 0 to 8, Colour to analyse the skin colour which can be seen by the naked eyes, Diameter – If the diameter is greater that 6mm then the cancerous possibilities are higher, Evolving of the mole is noted. These are the ABCDE features which are considered for the identification of melanoma or non-melanoma. The Statistical features are extracted from the enhanced image. Gray level Co-occurrence Matrix (GLCM) is formulated to obtain statistical features. In this paper we have analysed both ABCDE features and Statistical Features.

2.6 Classification

The Classification of Melanoma and Non-Melanoma using dermatoscopy images is done using machine learning algorithms like FFNN, SVM, KNN. The implementation algorithms are given in below.

1. The implementation of feed forward neural network is by obtaining the ABCD features (4), statistical features (11), and ABCD + statistical features (15) are given as the classifier input. In this network weights are set initially and the numbers of extracted features 4, 11, 15 are given as the input neurons. The hidden neurons in the network are given as 20. Target 2 is set in the output layer to detect whether the output is melanoma or non-melanoma.
2. The implementation of support vector machine is given as follows - The ABCD features (4), statistical features (11), and ABCD + statistical features (15) are

given as the classifier input. The kernel function used is linear kernel. The kernel scale is 1.

3. The implementation of K-nearest neighbour classifier has the ABCD features (4), statistical features (4), and ABCD + statistical features (15) are given as the classifier input. The K is initialized as 5.

2.7 Performance Analysis

Performance analysed using Accuracy, Sensitivity, Specificity, Negative and Positive Predictive Value and manually by TDS.

$$AC = \frac{N_{tp} + N_{tn}}{N_{tp} + N_{fp} + N_{fn} + N_{tn}}$$

$$SE = \frac{N_{tp}}{N_{tp} + N_{fn}}$$

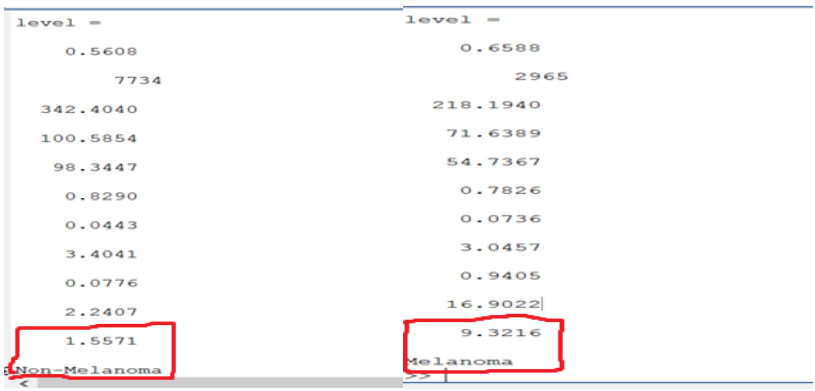
$$SP = \frac{N_{tn}}{N_{tn} + N_{fp}}$$

Where, *Ntp, Ntn, Nfp, Nfn* denote the number of true positive, true negative, false positive and false negative, respectively and they are all defined on the pixel level.
TDS is an important tool used in the diagnosis of melanoma. Calculation of TDS is based on ABCD rule. If TDS is less than 4.75 then it is non- melanoma, If TDS is greater than 5.45 than it is melanoma and if TDS is between 4.75 and 5.45 then it is the suspicious case of skin lesion. The resultant sample image is shown in fig 6.

$$TDS = 1.3*IrA + 0.1*IrB + 0.5*IrC + 0.5*IrD$$

From the obtained TDS score, the accuracy is manually calculated by

$$AC = \frac{\text{Correctly Classified Images} * 100}{\text{Total Image}}$$



a) Melanoma **b)** Non-Melanoma

Fig 6: Resultant Sample Image of TDS. a) Melanoma b) Non-Melanoma

The performance analysis is done by 9 different cases which are mentioned in table 1 and the results are tabulated in table 2.

CASES		AC	SE	SP	PPV	NPV
CASE 1	**Manual**	85%	-	-	-	-
CASE 2	**Manual**	86.4%	-	-	-	-
CASE 3	**FFNN**	90%	95.7%	81.8%	88.2%	93.1%
	SVM	88.1%	99.2%	72.7%	86.9%	90.8%
	KNN	87.6%	97%	74%	87.7%	87.6%
CASE 4	**FFNN**	90.6%	96%	82.9%	88.9%	93.55
	SVM	88.7%	95.3%	81%	86.4%	96.7%
	KNN	87.2%	91.4%	86.4%	85.5%	91.6%
CASE 5	**FFNN**	93.5%	96%	88.6%	86.3%	92.5%
	SVM	92%	96.7%	87.6%	88.5%	93.3%
	KNN	91%	97.8%	87.9%	86.3%	96.3%
CASE 6	**FFNN**	95.5%	94%	86.4%	83.2%	95%
	SVM	92.7%	95.2%	86.1%	84.3%	91.9%
	KNN	89.8%	96.2%	79.5%	82.9%	92.6%
CASE 7	**FFNN**	94.1%	94%	85.7%	87.3%	91%
	SVM	93.5%	97%	84.5%	87.9%	93.9%
	KNN	91.2%	98.2%	83.4%	87.5%	96.6%
CASE 8	**FFNN**	96.7%	87.1%	95.3%	89.2%	94.5%
	SVM	95.4%	98%	87.2%	86.4%	94.3%
	KNN	93.6%	96.9%	87.6%	84%	92.6%
CASE 9	**FFNN**	95.9%	97.3%	86.5%	85.9%	94.1%
	SVM	94.7%	96%	88.6%	81.4%	92.3%
	KNN	92.9%	96%	85.3%	89.6%	97.5%

Table 2: Performance Analysis of 9 Classification Cases

3 Conclusion

The proposed method uses MedNode Image Dataset as the input and is enhanced by bottom hat filter then, the lesion is segmented by Otsu Thresholding, Morphological method. The Features extracted are ABCD and Statistical features. Then the features are given to the classifiers FFNN, SVM and KNN and the performance are analysed by 9 different cases. The accuracy obtained 96.7% is higher compared to all other cases.

References

[1] L. Song, J. Lin, Z. J. Wang and H. Wang, "An End-to-End Multi-Task Deep Learning Framework for Skin Lesion Analysis," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 10, pp. 2912-2921, Oct. 2020.

[2] Yu, Lequan, et al. "Automated melanoma recognition in dermoscopy images via very deep residual networks." IEEE transactions on medical imaging 36.4 (2017): 994-1004

[3] MohdAnas, Ram Kailash Gupta, Dr. Shafeeq Ahmad, "Skin Cancer Classification Using K-Means Clustering", International Journal of Technical Research and Applications, Volume 5, Issue 1, 2017.

[4] Ramya, V. & Navarajan, J. & Prathipa, R. & Kumar, L Ashok. (2015). Detection of melanoma skin cancer using digital camera images. ARPN Journal of Engineering and Applied Sciences. 10. 3082-3085.

[5] Premaladha, J., Ravichandran, K.S. Novel Approaches for Diagnosing Melanoma Skin Lesions through Supervised and Deep Learning Algorithms. J Med Syst 40, 96 (2016).

[6] J. Bian, S. Zhang, S. Wang, J. Zhang and J. Guo, "Skin Lesion Classification by Multi-View Filtered Transfer Learning," in IEEE Access, vol. 9, pp. 66052-66061, 2021.

[7] Z. Yu et al., "Melanoma Recognition in Dermoscopy Images via Aggregated Deep Convolutional Features," in IEEE Transactions on Biomedical Engineering, vol. 66, no. 4, pp. 1006-1016, April 2019.
[8] F. Xie, H. Fan, Y. Li, Z. Jiang, R. Meng and A. Bovik, "Melanoma Classification on Dermoscopy Images Using a Neural Network Ensemble Model," in IEEE Transactions on Medical Imaging, vol. 36, no. 3, pp. 849-858, March 2017.
[9] B. A. Albert, "Deep Learning from Limited Training Data: Novel Segmentation and Ensemble Algorithms Applied to Automatic Melanoma Diagnosis," in IEEE Access, vol. 8, pp. 31254-31269, 2020.
[10] M. D. Alahmadi, "Multiscale Attention U-Net for Skin Lesion Segmentation," in IEEE Access, vol. 10, pp. 59145-59154, 2022.
[11] N. C. F. Codella et al., "Deep learning ensembles for melanoma recognition in dermoscopy images," in IBM Journal of Research and Development, vol. 61, no. 4/5, pp. 5:1-5:15, 1 July-Sept. 2017.
[12] L. Wei, K. Ding and H. Hu, "Automatic Skin Cancer Detection in Dermoscopy Images Based on Ensemble Lightweight Deep Learning Network," in IEEE Access, vol. 8, pp. 99633-99647, 2020.
[13] R. Ashraf et al., "Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection," in IEEE Access, vol. 8, pp. 147858-147871, 2020.
[14] L. D. Biasi, A. A. Citarella, M. Risi and G. Tortora, "A Cloud Approach for Melanoma Detection Based on Deep Learning Networks," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 962-972, March 2022.
[15] M. A. Kassem, K. M. Hosny and M. M. Fouad, "Skin Lesions Classification Into Eight Classes for ISIC 2019 Using Deep Convolutional Neural Network and Transfer Learning," in IEEE Access, vol. 8, pp. 114822-114832, 2020.
[16] A. Sáez, J. Sánchez-Monedero, P. A. Gutiérrez and C. Hervás-Martínez, "Machine Learning Methods for Binary and Multiclass Classification of Melanoma Thickness From Dermoscopic Images," in IEEE Transactions on Medical Imaging, vol. 35, no. 4, pp. 1036-1045, April 2016.