

Diagnosis of skin cancer using machine learning techniques

A. Murugan^a, Dr. S. Anu H Nair^b, Dr. A. Angelin Peace Preethi^c, Dr. K. P. Sanal Kumar^{d,*}

^a Department of Computer and Information Sciences, Annamalai University, Chidambaram, India

^b Department of CSE, Annamalai University, Chidambaram, India (Deputed to WPT Chennai)

^c Department of ECE, Karpagam college of Engineering, Anna University, India

^d PG Department of Computer Science, R. V. Government Arts College, Chengalpattu, India

ARTICLE INFO

Keywords:

Skin cancer
GLCM
GLRLM
Moment invariants
SVM

ABSTRACT

Generally, skin disease is a common one in human diseases. In computer vision application, the skin color is the powerful indication for this disease. This system identifies the skin cancer disease based on the images of skin. Initially, the skin is filtered using median filter and segmented using Mean shift segmentation. Segmented images are fed as input to feature extraction. GLCM, Moment Invariants and GLRLM features are extracted in this research work. The extracted features are classified by using classification techniques like Support vector machine, Probabilistic Neural Networks and Random forest and Combined SVM+ RF classifiers. Here combined SVM+RF classifier provided better results than other classifiers.

1. Introduction

Cancer is a disease which involves the atypical cell growth with the imminent to spread or enter into other parts of the body. Among the other cancers, harmful and dangerous form of cancer is the skin cancer. The skin cancer is curable only if it is identified in the initial stage. In the human body, skin plays a vital role in covering the entire parts of a body like muscles and bones. If there is a slight change in the functioning of the skin, it will affect the entire system of the body and thus plays a significant role. The diseased spot on the skin is called is called a lesion area. There is a wide variety of skin lesions. Each lesion is split according to its origin, i.e., the type of skin cells responsible for its genesis. Melanocytic lesions, like melanoma, develop from melanocytes, are important for the making of a protein pigment called melanin [1]. Non-melanocytic lesions have origin in other types of skin cells, such as the basal or the squamous cells. The distinction between the two types of lesions is visually performed, based on the presence or absence of a set of dermoscopic features, such as pigment network. The next step involves the identification of the lesion type, i.e., if it is a malignant neoplasm or a benign lesion. If the lesion belongs to the latter group, it is then classified into one of the different types of skin lesions. These decisions are also performed based on a set of dermoscopic characteristics. Skin lesions are the principal clinical signs of skin diseases such as Seborrheic keratosis, melanoma, Basal cell carcinoma etc. Basal cell carcinoma is noncancerous (benign) skin growths that some people develop as they grow old [2]. Non-melanoma and melanoma are the two basic types of skin cancer

which are seriously dangerous and also rarer. Melanoma is a malignancy occurs predominantly in white people, for men in the trunk and for the women in the lower limb but can seem to be in other body parts also.

More than twelve million people are suffering from cancer and the treatment to cure skin cancer remains the foremost tasks of modern medicine. Computer-aided detection helps in detecting skin cancer at an early stage. It is generally detected by doctors by the biopsy method to diagnosis the diseases. In the Biopsy method, the skin is scrapped or detached and these skin samples will undertake many laboratory tests. Because of this, this procedure is time-consuming and also painful. In the skin, one may develop symptoms like depigmentation which is like scar, blue-white veil, multiple blue-gray dots, pseudopods, multiple brown dots, globules, pigmented network [3]. Macroscopic images are generally branded as quantifiable images which are normally used to do the analysis computationally and these images are attained with common digital camera or video [4]. There are some problems with the clinical images such as poor resolution and the presence of objects such as skin lines, shadows, replications and the hair in the images. Because of these problems, it is very challenging to study skin lesions. In the computational method, there are many steps involved in diagnosing the skin cancer such as pre-processing, image segmentation, feature extraction, feature deduction and classification. In this paper, each step involved in detecting the skin cancer and associated methods are discussed. For the classification, SVM, Random Forest, PNN and the fusion of the classifiers SVM and RF are used.

The proposed model in this paper identifies the lesion from the

* Corresponding author.

dermoscopic images and detects the skin diseases. The classes of skin diseases being dealt in this paper are namely lentigo simplex, solar lentigo, nevus, melanocytic nevi, seborrheic, melanoma, basal cell carcinoma and blue nevus to identify the classification accurately.

Seborrheic keratosis develops in the aged people and usually can be seen in chest, shoulders or on the back but can occur on any part of the body. It may grow in single or as a group and occur slowly. The appearance may vary like light tan to brown or black in color, rough texture or may be smooth. They stick on to the skin and size is very small to more than 1 inch (2.5 cm) across. Sometimes, it may be mistaken for moles, warts.

Basal cell carcinoma is a tumor which develops when the skin is much unprotected towards sunlight. This type of cancer can move to the nearby bone and the tissue under the skin but it is improbable to spread from the skin to other parts of the body. These grow as small bumps which are shiny and mostly in the nose or in the face but can occur in other parts of the body also. It grows usually very slow and doesn't show proximally.

Melanoma is a type of skin cancer which occurs when the melanocyte pigment-producing cells become cancerous. Utmost, the pigment cells are seen in the skin but it can occur in and other parts of the body and in eyes. It may appear on face, chest and or on back. For the women, it is developed in the legs

The classes of skin cancer taken for analysis in this work are given in the Fig. 1. Among all the classes of skin cancer, melanoma is the dangerous cancer which spreads other parts of the body quickly and makes severer damage to the tissues. Seborrhoea keratosis is not a cancerous disease and can be cured. But people may often confuse this with melanoma.

This paper is organized as follows. The various diagnosis methodologies proposed in the literature are given in the Section 2. Section 3 describes the proposed model used for skin cancer detection. The experimental results and the performance analysis of the classifiers used in this paper are given in the Section 4 and finally, conclusion is given in the Section 5.

2. Related work

During the last few decades, many recent years many methodologies have been developed in skin cancer detection. Many of these techniques use different pattern identification techniques to detect the disease [5]. One of the methods is the computer-aided diagnosis (CAD) system presented by Schmid et al., for detecting the lesion boundary and quantification of the amount. [6]. He used a collection of benign and malignant lesions which are stored in the database along with the histopathology and is served as a reference database. This delivers the information to the physicians during the diagnosis stage.

Celebi et al., stated a methodology to classify the pigmented lesion. In order to separate the lesion clearly, automatic border detection and the shape features are also extracted from the border. Using the Euclidean distance transform, image is split into various substantial regions to extract the color and texture related features and fed into an

optimization framework to rank the features [7].

Affi et al., developed an optimized embedded SVM classifier for early detection of skin cancer using a minimum cost handheld device. The authors proposed a methodology involving hardware/software to know the melanoma discovery on a chip by employing the SVM classifier onto FPGA. The proposed design technology uses Ultra-Fast High-Level Synthesis. This technology gives an effective classification of the melanoma on a chip [8].

Garg et al., proposed a methodology which uses a pre-processing of the image to filter and remove the extra noise existing in the image. The skin lesion is exposed to segmentation and the features are extracted using various parameters like asymmetry, border irregularity, color, and diameter of the lesion using the ABCD rule. [9]. Kasmiet al., implemented automatic ABCD recording of lesions to discriminate malignant melanoma from benign lesions. The authors extracted Blue-white veil, Geometrical Properties and Pigment Network for variance Structures. In this work, artefacts are removed using the median filter and the thick hairs are identified with the help of Gabor filters with different orientations and frequencies. Linear Interpolation repairs image based on the hair mask. GAC is used for Lesions segmentation. color, shape and luminance asymmetry forms the basis for A's core. Blue-white veil structures, network and Lesion geometrical properties have relied on the D attribute. [10].

Fekracheet. al., used Ant Colony Based Segmentation for segmenting the dermoscopic image. And the features extracted are Shape, Colour and Texture. KNN and ANN are the classification techniques used by the authors to classify the lesions [11]. Abbas et al., accommodated CASH features and Sequential floating forward selection for developing a complete diagnostic system. Thresholding and improved Dynamic Programming are used for the segmentation. The features extracted are Border, Asymmetry, Irregularity, Colour and Differential structures and the SVM classifier is used to classify the lesions [12]. Oliveira et al., proposed an approach to minimize the noise exist in the image considered for analysis by using Anisotropic diffusion filter and a support vector machine (SVM) classifier to classify the skin lesions [13]. Sumithra et al., proposed a technique for automatic segmentation and classification of skin lesions. The undesirable hairs and noise are removed and then a region growing segmentation method is applied to extract color and texture features from the lesion [14]. The extracted features are classified using the fusion of SVM and k-NN classifiers. Murugan et al., proposed a methodology for detecting skin cancer. For segmenting the lesion, they used watershed algorithm and the features are extracted using ABCD rule and GLCM. The extracted features are classified using KNN, Random forest and SVM.

From the literature, it is observed that many works have been done mostly for the melanoma cancer. In this paper, we focus not only on melanoma but also on other classes of skin cancer.

3. Proposed model

Diagnosing the skin cancer comprises various stages. The stages are 1) image pre-processing, 2) lesion segmentation, 3) feature extraction,

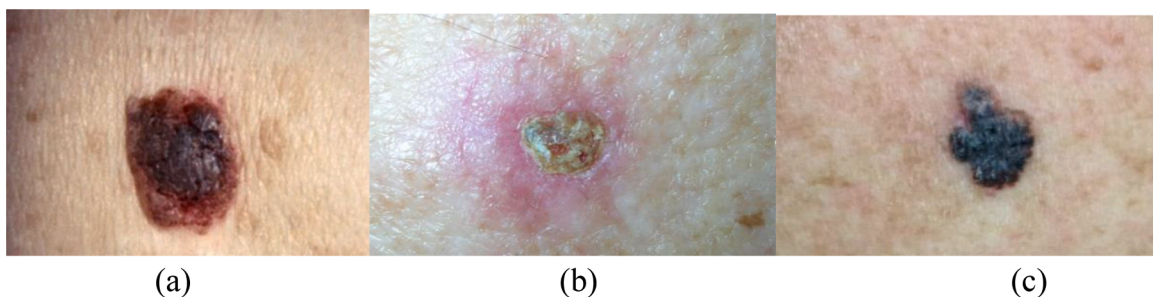


Fig 1. (a) Seborrheic keratosis (b) Basal cell carcinoma (c) Melanoma.

and 4) classification as shown in Fig. 2. In this section, each step of the diagnosis process is discussed.

3.1. Image pre-processing

The quality of the image taken for detection is improved in the pre-processing stage. In this stage, irrelevant noises in the images such as hair, bubbles are removed. Since these noises will cause inaccuracy in the classification. In order to remove the noises in the images, various filters are used in the literature such as median filter, mean filter, Gaussian filter, adaptive median filter and adaptive wiener filter for denoising from various noises like Gaussian, salt and pepper, Poisson and speckle noise. In this work, median filter is used to remove the noise in the image.

Median Filter

The median filter removes bubbles which exists in the lesion. The bubbles may disturb in measuring the asymmetry intensity and the color [15]. The effect of bubbles in the image and the thin hair is removed by using $[3 \times 3]$ median filter. Experimentally, the size of the median filter was decided. The size is determined by obtaining two goals: lessening of bubbles amount and preventing the fuzzy edges.

3.2. Image segmentation

In this Segmentation stage, it separates the ROI image from the background. It is a region in which lesion is examined. The resultant of the step separates the cancerous portion of the image and the healthy portion of the image. There are four main types of segmentation methods namely Threshold base, Region-based, Pixel-based and Model-based. In this work, the mean shift segmentation method [16] is used to separates the tumorous parts since it can preserve the local boundaries precisely.

3.3. Mean shift image segmentation algorithm

In the mean shift segmentation algorithm, feature points are moved towards the significant nodes and automatically cluster themselves. This method, initially gets the vital features of interest in the intensity of the

image and also the stationary points. The pixels are clustered in to different cluster regions after getting the density of the image intensity and the modes of the image intensity. The algorithm is given below.

Step 1. Let x_i and z_i , $i = 1, \dots, n$, be the D -dimensional input and filtered image pixels in the joint spatial-range domain and L_i the label of the i^{th} pixel in the segmented image.

Step 2. Run the mean shift filtering procedure for the image and store all the information about the D -dimensional convergence point in z_i , i.e., $z_i = Y_{i,c}$.

Step 3. Delineate in the joint domain the clusters $\{C_p\}_{p=1 \dots m}$ by grouping together all z_i which are closer than K_{in} in the spatial domain and K_{r} in the range domain, i.e., concatenate the basins of attraction of corresponding convergence points.

Step 4. For each $i = 1, \dots, n$, assign $L_i = \{p/z_i \in C_p\}$.

Step 5. Optional: eliminate spatial regions containing less than M pixels.

3.4. Feature extraction

The feature extraction starts after the pre-processing steps. After the pigmented lesion is segmented, necessary features have to be extracted. In this research work, feature extraction methods like Moments Invariant features, gray Level Co-Occurrence Matrix (GLCM) feature and Gray Level Run Length Matrix (GLRLM) were extracted.

Moments Invariants

The first feature extraction method is the moment invariants (MIs) [17] which is able to maintain the ability of moment invariants in providing unique and distinguishable features in a skin lesion. The MIs are well-known to be invariant are evaluated using central moments of the image function $f(x, y)$ up to third order which is used as features.

Let $M \times M$ be two dimensional moments of a dermoscopic image which has a gray function $f(x, y)$. Where the values of x and y are from 0 to $M-1$ i.e. (0, 1, 2, ..., $M-1$) which is given as in eq.

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} (x^p) \cdot (y^q) f(x, y) \quad p, q = 0, 1, 2, 3 \quad (1)$$

The moments function $f(x, y)$ transformed through a quantity (a, b) is

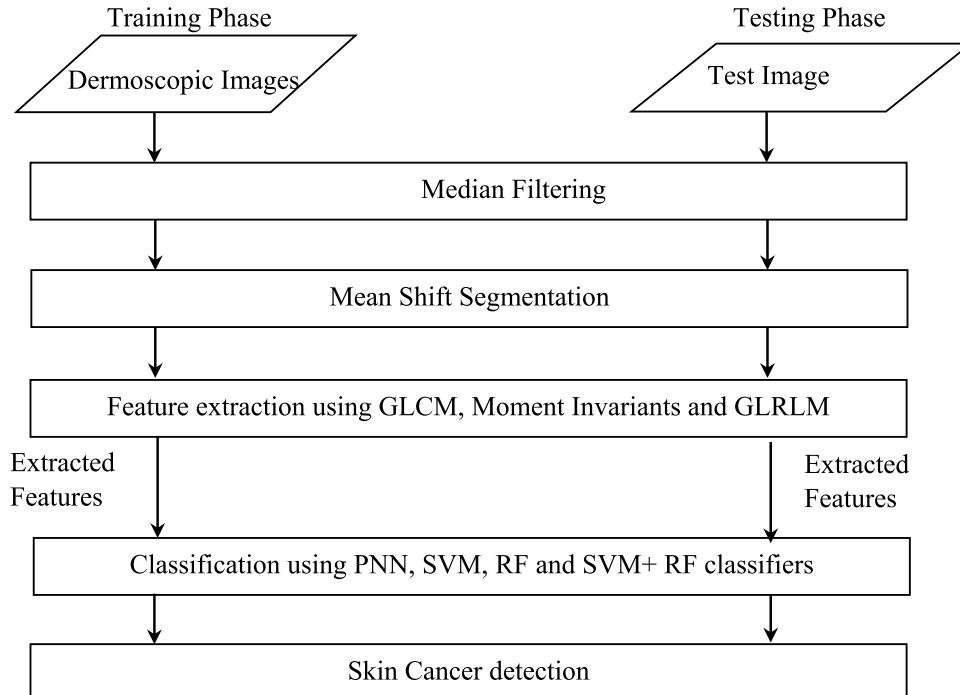


Fig 2. Proposed Model.

given in eq. (2).

$$\mu_{pq} = \sum_x \sum_y (x+a)^p \cdot (y+b)^q f(x,y) \quad (2)$$

In accordance with the normalised central moments which are invariant to order three namely position of the object, scale of the object and the object orientation. The seven moments are given in eq. (3).

$$\begin{aligned} M_1 &= (\eta_{20} + \eta_{02}) \\ M_2 &= (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2 \\ M_3 &= (\eta_{30} + 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\ M_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} - \eta_{03})^2 \\ M_5 &= (\eta_{30} + 3\eta_{12})(\eta_{30} + \eta_{12})(\eta_{30} + \eta_{12})^2 - 3[(\eta_{21} + \eta_{03})^2] \\ &\quad + (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ M_6 &= [(\eta_{20} + \eta_{02})(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\ M_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})(\eta_{30} + \eta_{12})^2 - [3(\eta_{21} + \eta_{03})^2] \\ &\quad - (\eta_{30} + 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]. \end{aligned} \quad (3)$$

Gray Level Co-Occurrence Matrix (GLCM)

Gray Level Co-Occurrence Matrix (GLCM) features are extracted using the statistical procedures. GLCM is a matrix of frequencies [18]. The matrix contents mainly depend on the direction and the distance relationship between pixels [19] and considers association among two pixels namely the reference pixel and the neighbor pixel. The number of rows and columns in the matrix is nothing but the number of gray level G in the given image. The different textural features are computed using GLCM matrix in four different orientation positions namely vertically, horizontally, or diagonally to adjacent the pixels. In this work, the different features used are entropy, energy, contrast, correlation, homogeneity, inverse difference moment, dissimilarity and maximum probability can be calculated using GLCM matrix.

Gray Level Run Length Matrix (GLRLM)

The third feature extraction method used in this research work is Gray Level Run Length Matrix [20] which captures the roughness of texture in stated ways. A run is a series of successive pixels of the same intensity along a precise linear positioning. Adequate textures incline to comprise more small runs with comparable intensities, while uneven textures have further long runs with considerably dissimilar intensities [21].

3.5. Classification

In order to classify a test sample from the set of known classes, it is important to use a classifier after the features are extracted from the skin lesion. Support Vector Machine (SVM), Probabilistic Neural Network (PNN) Random Forest and also the combined SVM with RF are used in this research work.

Support Vector Machines (SVM)

SVM is a machine learning algorithm which works on the basis of statistical theory [22]. In the literature, compared with the other machine learning algorithms, SVM performs better or par with the other machine learning algorithms. SVM solves constrained quadratic to differentiate two classes and the problem which has multiclass can also be solved. Building limiting boundaries in a dataset optimally, SVM algorithm does a good decision between two classes' limits. SVM algorithm maximizes the margin between the data points and the hyper planes.

The algorithm for Support Vector Machine is given below

Step 1. Divide the given data set into two set of data items having different class labels assigned to them

Step 2. Features and attributes are classified based on the labelled class

Step 3. Candidate Support Value Estimation

Step 4. While the instances value is not equal to null Repeat the following steps for all instances

Step 5. Support Value is equal to Similarity between each instance in the attribute Find Total Error Value

Step 6. If any instance is less than 0 then Estimate the decision value
Decision value = Support Value/Total Error

Step 7. Repeat the above steps until empty

Probabilistic Neural Network (PNN)

The PNN consists of several sub-networks. The set of measurements are considered as the input nodes in the network. The centres, the given data points are used to form the Gaussian functions which forms the second layer. The layer 3 in the network achieves an average process of the outputs from each class of the layer 2. By choosing the largest value, the layer 4 selects the maximum value by performing a vote. Then, the associated class label is predicted.

Algorithm to set up PNN

Step 1. Read in the file of training data set vectors & class numbers

Step 2. Arrange these values into the K sets and the class of vectors are in each set.

Step 3. For each k, a Gaussian function is centered and defined on each training data vector in set k

Step 4. Describe summed Gaussian output function

After defining the PNN, the vectors of lesions are fed to the network and the classification is done as given in the below algorithm.

Algorithm for Classification

Step 1. Read input lesion vector and provide it to the Gaussian function of each class

Step 2. For the hidden nodes in each group, calculate the Gaussian functional value at each of the hidden nodes.

Step 3. The calculated Gaussian functional values of each hidden node in the group will be taken as single class output for that hidden group

Step 4. Sum all the inputs and multiply by a constant value at each class output node

Step 5. Obtain the greatest value of all the summed functional values at the output nodes

Random Forest

It is the supervised classification algorithm. This algorithm forms a forest. If there are more number of trees in the forest, the forest is strong like that this classifier also gives accurate results when the number of trees are greater in number.

The random forests algorithm for the classification is as follows:

Step 1. Draw n tree bootstrap samples from the skin lesion.

Step 2. For each of the bootstrap samples, grow an un pruned classification tree

Step 3. At each node, rather than choosing the best split among all predictors, randomly sample m_{try} of the predictors and choose the best split from among those variables. (Bagging can be thought of as the special case of random forests obtained when $m_{try} = b$, the number of predictors.)

Step 4. Predict new data by aggregating the predictions of the n trees i.e., majority votes

Combined Support Vector Machine with Random Forest Classifier

The skin lesions are classified using both SVM and RF as a combined classifier. In the fused classifier, the image data set is split in to subsets in a random way. Each data item in each of the subset has a weight factor associated with it. The skin lesions in the subsets are classified by using SVM. The occurrence of misclassification increases the weight factor. If not, the weight factor is decreased. The subsets are sorted and the SVM classifier classifies the lesion in each subset. Based on the classification accuracy, the weights are updated again. These steps are repetitive until the value of the weight is very low. The output of the input data set is calculated by employing voting methodology. The voting is applied to all the random subsets classification outputs.

The algorithm for the fusion of Random forest and SVM classifier is given below.

Step 1. Weight is initialized to each data set.

Step 2. Create a new data feature subset from the data set using

random replacement method.

Step 3. For each random feature subset Apply SVM to each feature subset

Step 4. Generate the classification output

Step 5. Update the weights of all the data vectors in the training set depending on the classification outcome. If an example was misclassified then its weight is increased [or else the weight is decreased].

Step 6. Repeat steps 1 to 5 by regenerating random subsets till all the input data vectors are appropriately classified or apply iteration limit.

Step 7. Compute output of the complete data set by applying majority voting mechanism among the final outputs of each of the Random feature subsets D_i of The original set D obtained after Step 6.

4. Results and discussions

The dataset used in this work to evaluate the performance of the classifiers is International Skin Imaging Collaboration (ISIC). The total number of images taken for the experimentation is 1000 and 10 cross fold validation is used where all samples were trained and tested. In this paper, four different classification tasks are done for skin lesion classification. The lesion is classified to detect and distinguish from Seborrhoea keratosis, Melanoma, Basal Cell Carcinoma and benign lesion. The performance of the classifications used in this research work is evaluated based on the metrics such as accuracy, sensitivity and specificity.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \quad (4)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \quad (5)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100\% \quad (6)$$

Where the TP, TN, FP, FN in Eq. (4), 5, and 6 are True Positive, True Negative, False Positive and False Negative respectively.

Table 1 and Fig. 3 depicts the accuracy of various classifiers. It is inferred that combined SVM+RF provided better results.

Table 2 and Fig. 4 depicts the sensitivity of various classifiers. It is inferred that SVM+RF provided better results.

Table 3 and Fig. 5 depicts the specificity of various classifiers. It is inferred that combined SVM+RF provided better results.

The key criteria to evaluate the performance of the classifier in detecting cancer are accuracy, specificity and sensitivity. It is obvious from the results that the proposed SVM+RF classifier can accomplish the maximum sensitivity, specificity and accuracy compared to other classifiers used in this paper. The proposed model with the SVM+RF classifier also maintains a substantial score when compared to the other classifiers. The accuracy obtained by this fused classifier is 86.12% for GLRLM feature and 84.63% for Moment Invariant feature and 89.31% for GLCM feature. This result is primarily due to the improvement done in the border detection and proper choice and deployment of a set of discriminative and operational features.

5. Conclusion

In this research paper, skin cancer detection system using image processing is proposed and it is an improved diagnosis approach than the

Table 1
Accuracy of various Classifiers.

FeaturesClassifiers	GLCM	MOMENT INVARIANT	GLRLM
PNN	63.25	56.94	61.93
RF	76.36	69.31	71.25
SVM	87.8	82.26	84.7
SVM+RF	89.31	84.63	86.12

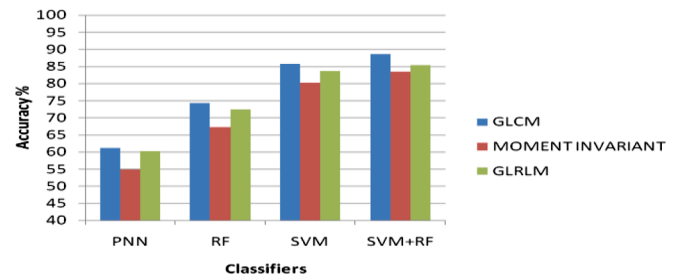


Fig 3. Accuracy of various classifiers.

Table 2
Sensitivity of various Classifiers.

FeaturesClassifiers	GLCM	MOMENT INVARIANT	GLRLM
PNN	61.17	54.86	60.18
RF	74.28	67.23	72.44
SVM	85.72	80.18	83.62
SVM+RF	88.56	83.49	85.31

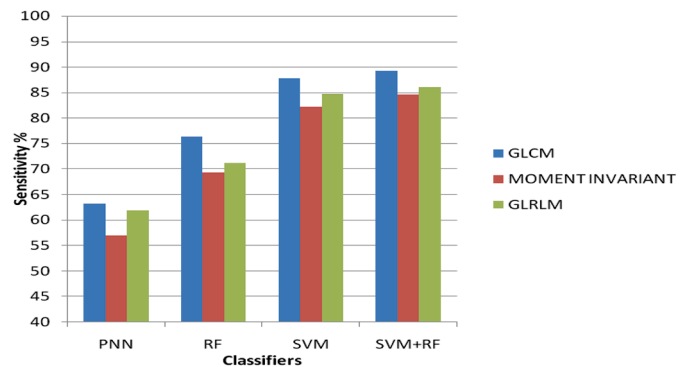


Fig 4. Sensitivity of various classifiers.

Table 3
Specificity of various Classifiers.

FeaturesClassifiers	GLCM	MOMENT INVARIANT	GLRLM
PNN	59.09	52.78	58.43
RF	72.2	65.15	73.63
SVM	83.64	78.1	82.54
SVM+RF	87.81	82.35	84.5

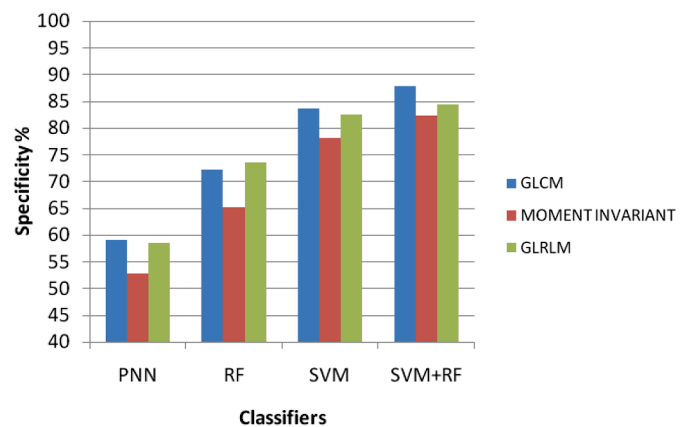


Fig 5. Specificity of various classifiers.

traditional Biopsy method. The computer technology based detection of skin cancer is more beneficial to patients. In this, the patients can ascertain the skin cancer in a very effective and accurate way while saving their time and prepares them for the treatment. In this paper, the diagnosing method uses an image processing methodology. The pre-processing of the identified skin region is done by the median filter and the mean shift segmentation method is used to separate the affected area from the healthy skin. The features were extracted using Moment Invariant features, Gray Level Co-occurrence Matrix (GLCM) feature and the Gray Level Run Length Matrix (GLRLM). These extracted features are classified using SVM, PNN, RF and Combined SVM + RF for detection of skin disease. Here Combined SVM+RF outperform than other classifiers and the accuracy of classifier is 86.12% for GLRLM feature and 84.63% for Moment Invariant feature and 89.31% for GLCM feature.

Declaration of Competing Interest

The authors have no conflict of interests and the paper has not been submitted elsewhere.

References

- [1] Andre G.C. Pacheco, Renato A. Krohling, The impact of patient clinical information on automated skin cancer detection, *Comput. Biol. Med.* 116 (2020), <https://doi.org/10.1016/j.combiomed.2019.103545>, 103545/ISSN 0010-4825.
- [2] Shilpa Saravanan, B. Heshma, A.V. Ashma Shanofar, R. Vanithamani, "Skin cancer detection using dermoscope images, Materials Today: Proceedings, 2020, ISSN 2214-7853, 10.1016/j.matpr.2020.08.388.
- [3] Palak Mehta, Bhumika Shah, Review on techniques and steps of computer aided skin cancer diagnosis, *Procedia Comput Sci* 85 (2016) 309–316.
- [4] Sameena Pathan, K. GopalakrishnaPrabhu, P.C. Siddalingaswamy, Techniques and algorithms for computer aided diagnosis of pigmented skin lesions—A review, *Biomed Signal Process Control* 39 (2018) 237–262.
- [5] M. Gurcan, T. Pan, H. Shimada, and J. Saltz, "Image analysis for neuroblastoma classification: segmentation of cell nuclei," in *Proc. 28th IEEE Annu. Int. Conf. EMBS*, 2006, pp. 4844–4847.
- [6] Philippe Schmid-Saugeon, Joël Guilloeb, Jean-Philippe Thirana, Towards a computer-aided diagnosis system for pigmented skin lesions, *Computerized Medical Imaging and Graphics* 27 (1) (2003) 65–78.
- [7] M.Emre Celebi, et al., A methodological approach to the classification of dermoscopy images, *Computerized Medical imaging and graphics* 31 (6) (2007) 362–373.
- [8] Shereen Afifi, Hamid GholamHosseini, Roopak Sinha, A system on chip for melanoma detection using FPGA-based SVM classifier, *Microprocess Microsyst* 65 (2019) 57–68.
- [9] Nishtha Garg, Vishakha Sharma, Prabhjot Kaur, Melanoma skin cancer detection using image processing, *Sensors and Image Processing*, Springer, Singapore, 2018, pp. 111–119.
- [10] R. Kasmi, K. Mokrani, Classification of malignant melanoma and benign skin lesions: implementation of automatic ABCD rule, *IET Image Proc* 10 (6) (2016) 448–455.
- [11] Fekache Dalila, Ameur Zohra, Kasmi Reda, CherifiHocine, Segmentation and classification of melanoma and benign skin lesions, *Optik – Int. J. Light Electron Opt.* (2017).
- [12] Q. Abbas, M. EmreCelebi, L.F. Garcia, W. Ahmad, Melanoma recognition framework based on expert definition of ABCD for dermoscopic images, *Skin Res. Technol.* 19 (1) (2013) e93–e102.
- [13] Roberta B. Oliveira, et al., A computational approach for detecting pigmented skin lesions in macroscopic images, *Expert Syst Appl* 61 (2016) 53–63.
- [14] R. Sumithra, Mahamad Suhil, D.S. Guru, Segmentation and classification of skin lesions for disease diagnosis, *Procedia Comput Sci* 45 (2015) 76–85.
- [15] A. Murugan, S. Anu H. Nair, K.P. Sanal Kumar, Detection of skin cancer using SVM, random forest and KNN classifiers, *J Med Syst* 43 (8) (2019) 269.
- [16] S.E. Umbaugh, *Computer imaging: Digital Image Analysis and Processing*, CRC Press, Boca Raton, FL, 2005.
- [17] E. Zhou, Huiyu, et al., Gradient vector flow with mean shift for skin lesion segmentation, *Computerized Medical Imaging and Graphics* 35 (2) (2011) 121–127.
- [18] Ming-Kuei. Hu, Visual pattern recognition by moment invariants, *IRE transactions on information theory* 8 (2) (1962) 179–187.
- [19] Ebtihal Almansour, M. ArfanJaffar, Classification of dermoscopic skin cancer images using color and hybrid texture features, *IJCSNS Int J ComputSciNetwSecur* 16 (4) (2016) 135–139.
- [20] Robert M. Haralick, Karthikeyan Shanmugam, Its' HakDinstein, Textural features for image classification, *Systems, Man and Cybernetics* 6 (1973) 610–621. *IEEE Transactions on*.
- [21] Al-Kadi OS, Texture measures combination for improved meningioma classification of histopathological images, *Pattern Recognit* 43 (2010) 2043–2053.
- [22] Palak Mehta, Bhumika Shah, Review on techniques and steps of computer aided skin cancer diagnosis, *Procedia Comput Sci* 85 (2016) 309–316.



A. Murugan is an Assistant professor in the Department of Computer science of Thiru kolanjiappar Government Arts College, Viridhachalam. He is pursuing Ph.D in Computer Science at Annamalai university Chidambaram. His research interest includes Medical Image processing, Data Mining etc. .



Dr. S. Anu H Nair is an Assistant Professor in the Department of Computer Science and Engineering of Annamalai University from 2005. She received her Master Degree from Manonmaniam Sundaranar University, Tirunelveli and the Ph.D degree from Annamalai University, Chidambaram, India. Her main research areas include image processing, pattern classification techniques and neural networks. She has published thirty research papers on these topics in International journals and conferences and two book chapters too .



Dr. Angelin Peace Preethi has obtained her Ph.D degree from Anna University, Chennai. She received Bachelor of Engineering in Anna University and Master of Technology in Karunya University, Coimbatore. She has published many research papers in International Journals and Conferences .



Dr. K.P. Sanal Kumar received the M.C.A., degree from M.S. University, Tirunelveli in 2000. He received the M.Tech degree in Computer Science and Engineering from Bharath University, Chennai in the year 2005. . He received the M.Phil degree in Computer Science from M.S. University, Tirunelveli in the year 2008. He received his Ph.D in Computer Science and Engineering from Annamalai University in 2019. He has been with Annamalai University, since 2008. Currently he is working as Assistant Professor in the Department of Computer science at R. V. Government college, Chengalpattu, TamilNadu. He has published 30 papers in reputed international conferences and peer reviewed Journals. He is a life member of CSI and ISTE, IAENG. His research interest includes Digital Image Processing, Wearable Computing, Pattern Recognition and Artificial Intelligence etc. .