Image Pattern Analysis towards Classification of Skin Cancer through Dermoscopic Images

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***Abstract*—Malignant melanoma is one of the most dangerous forms of skin cancer. Death rates are quite high because of their proliferation ability to other body parts. Melanoma can be cured with early and correct diagnosis therefore there is a significant requirement of a system that can correctly differentiate benign and melanoma lesions. A computer-aided methodology for the classification of benign and melanoma is proposed in this study. To determine the area of interest of the lesion part, dermoscopic skin lesion images are first segmented using k-means clustering. Next, extensive feature extraction is performed on segmented images by using feature descriptors: local binary patterns (LBP), histogram of oriented gradients (HOG), and bag of visual words (BoVW). These features are evaluated on a wide range of classification methodologies. Experimental analysis reveals that BoVW features with support vector machines classifier yield the highest results in terms of 99.8% accuracy, 100% sensitivity, and 99.5% specificity.**

Keywords—skin lesion detection, skin cancer classification, feature extraction, classification, support vector machines

I. Introduction

Among 100s of types of cancer, the most harmful disease is skin cancer. It has the greatest number of patients throughout the globe. The cause of this cancer is the rapidly growing abnormal cells, which can form lumps in the skin, this will lead to skin tumors. There are about 132,000 melanoma skin cancer cases per year, according to the number provided by the World Health Organization.

Cancer is diagnosed by using a biopsy method. This test is done by scraping off a region of skin lesion and then tests are performed on it in the laboratory. It is a time taking and painful method for the patient. To overcome these consequences, computerized diagnosis is suggested to ease the pain which the patient faces through the process of biopsy. This process only requires the images of the affected part of the skin, so the patient must not face any physical pain. Hence, this process will minimize the agony for the patient. To diagnose Melanoma Skin Cancer, the procedure of computerized diagnosis uses the tools for image processing. Initially pre-processing is done by doing segmentation then the area of interest of the skin is separated from the image. After that, features are extracted from this segment using different feature extraction techniques. Finally, on the extracted features, classification is performed to classify the type of cancer as melanoma or ordinary skin cancer.

II. Literature Review

Extensive research has been conducted towards the early diagnosis of skin cancer using dermoscopic images. The most common technique used is hydride thresholding, using support vector machines (SVM), histogram, global thresholding, and computer-aided technology. Multiple techniques for feature extraction are used for image processing for example in [1] the author has used contrast enhancement to make it suitable for segmentation, then global thresholding is used for proper segmentations. Her accuracy is about 95%. Similarly, in [2] authors used **102** images for the detection of diseases. In this paper, the four-phase process is used for diagnoses of skin cancer. First is pre-processing (resizing of images and RGB to greyscale conversion), second is feature extraction using Grey Level Co-occurrence Matrices (GLCM), third is feature selection. Finally, the achieved classification accuracy was 93%. In [2] the author has performed a classification between Melanoma cancer lesion and normal skin. Different parameters are checked by The Lesion Image analysis tool like Asymmetry, Border, Color, Diameter, (ABCD), etc. these parameters are checked by different features such as texture, size, and shape, which are extracted from the segmentation process. The skin is then classified as Normal skin or Melanoma cancer by using these extracted feature parameters. The achieve

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classification accuracy is also very high but only one type of skin cancer is detected.

Similarly, in [3], the input dermoscopic image is first converted into grayscale. Image preprocessing for hair removal was performed through Gaussian filter and Otsu's Thresholding was used to lesion segmentation. Color, shape, and texture features were extracted to classify images through SVM classification. The best accuracy of 90.47% is reported through SVM with Linear Kernel. In [4], skin cancer classification through dermoscopic images is performed through a combination of median filtering for hair removal and k-means clustering for segmentation. Color, subregion, and text features were extracted to train SVM for image categorization. Accuracy of 96.8% was reported by the proposed model.

In paper [5], the segmentation is grounded on edge operators and active contours but this method has a very low computational complexity. Boundary and edges are not clearly defined by using this method. In paper [6], the comparison and segmentation are done using different methods. In paper [7], for the detection of the border, the watershed technique is used. In Paper [8], to segment the lesion, an automatic method is proposed. Otsu and local binary pattern (LBP) methods are used by the author for segmenting the texture. For Classification, 97% for sensitivity, and 93% for specificity was achieved by neural networks. Other types of lesions, such as NoMSLs, are not considered in this study.

In [9], a new feature extractor is proposed for the classification of skin lesions based on dermoscopic images. Images are first segmented through active contour segmentation, followed by texture and color feature extraction. Classification accuracy of 97% was achieved by training and testing support vector machines classifier. In [10] geometric features of skin lesion were extracted to detect and classification of skin cancer. Features such as border length, diameter and asymmetry parameters, area, perimeter, irregularity index were extracted. Characterization of skin cancer images is performed through K-Nearest Neighbor classification. 90% classification accuracy was achieved during experimentation. A non-invasive automated methodology for skin lesion detection is proposed in [11]. Early detection of melanoma was performed through SVM classification. Fast marching in the painting algorithm was used for image preprocessing.

Automated system for skin lesion classification and detection for four types of skin cancers: Melanoma, Basal cell carcinoma, actinic Keratosis, Squamous cell carcinoma is proposed in [12]. Feature extraction is performed through Grey Level Co-occurrence Matrices (GLCM) which are fed to multi-class SVM for distinguishing different classes. The proposed model achieved 84% classification accuracy. In another study [13], image enhancement is performed for skin lesion detection for smartphone-based applications. A median filter was employed to remove noise in which Gaussian filter was used for image smoothing.

In paper [14], deep learning for a fully automatic method for skin lesion classification is proposed.

Three pre-trained models such as AlexNet, VGG16, and ResNet-18 were employed to extracted deep features. Extracted features were fused and employed to train and test the SVM classifier. Several works [15] [16] [17] [18] tried to train a classical classifier by extracting deep features from the skin lesion images. Yet, there is a limitation to these studies, as a definite layer for extracting deep features is used or a definite pre-trained network architecture is used. Likewise, a single network limits the pre-trained network that is being used. In [16], the author has used a single pre-trained AlexNet while [15] custom a single pre-trained VGG16, and a single pre-trained Inception-v3 network [18] is utilized by [13].

III. Methods and Materials

A. System Overview

The architecture of the proposed skin lesion classification system is presented in Fig. 1. Skin lesion images are first preprocessed using k-mean clustering for detection of region of interest. Afterward, multiple features such as texture and Bag of Visual Words (BoVW) are extracted and fused to get precise and accurate image representation. These features are fed to Support Vector Machine (SVM) classification to distinguish between melanoma and benign images.

B. Dataset description

In this research, we evaluated our proposed methodology for skin lesion classification on HAM10000 dataset [19]. This dataset comprises of 11788 dermoscopic images collected from different populations in varying conditions. The original dataset consists of multiple categories of pigmented lesions. In this research, we used 2000 images from melanoma and benign categories. Sample images from each class are shown din Fig. 2a and Fig. 2b.

C. Image Preprocessing and Segmentation

To pre-process and extract region of interest from skin cancer dermoscopic image color based k-mean clustering is employed [20]. Generally, K-means divide the image pixels into a number of groups based on their means. To the extracted region of skin cancer lesion, the image is segmented into foreground and background using two centroids or means.

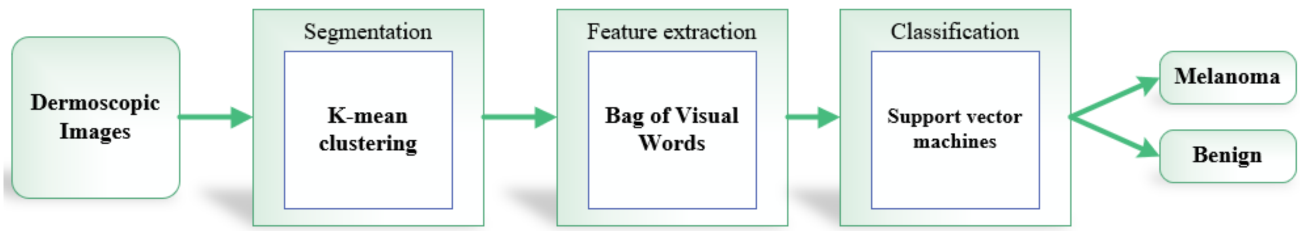

Fig. 1: Overview of the Proposed System

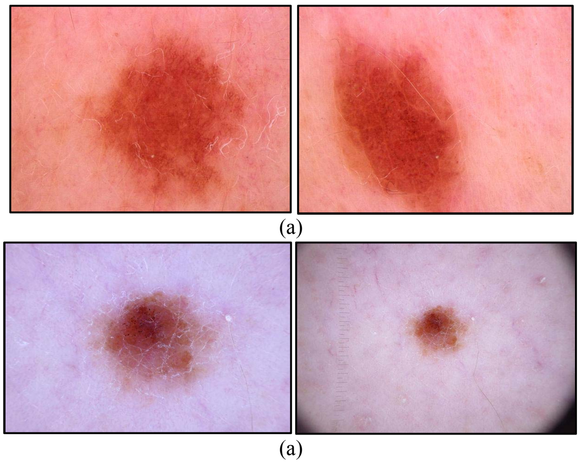

Fig. 2. (a) Example images of Benign. (b) Example images of Melanoma

K-means clustering algorithm partitions given data points into a k number of groups and consists of two processing steps.

1) In the first step, k-means algorithm calculates the k centroid.
2) It computes the distance of each data point from the centroid and takes it to that cluster where the distance is minimum.

After grouping, again centroids and computed and distances of each data point from the new centroid is measured.

K-means clustering algorithm is defined below:

1. Initialize centre points and number of clusters.
2. For each pixel in the dermoscopic image, compute Euclidean distance between center and each pixel of an image.

$$D = |p(x,y) - c_k| \tag{1}$$

3. Assign a class label to all pixels and again computer new value of center using the equation below.

$$c_k = \frac{1}{k}\sum_{y\in c_k}\sum_{x\in c_k} p(x,y) \tag{2}$$

4. Repeat the processing until the error is reduced or a specific number of iterations is completed.
5. Convert the cluster pixels into segmented image output.

Fig. 3a and 3b shows the segmented images of benign and melanoma classes respectively.

D. Feature Extraction

In this stage, representative features are extracted from skin lesion dermoscopic images of different categories. Local Binary Patterns (LBP), Histogram of oriented gradients (HOG) and Bag of visual words (BoVW) features are extracted and comparative analysis is performed.

1) Local Binary Patterns (LBP)

LBP is a local image feature descriptor widely adopted in the domain of computer vision [21, 22]. In a particular window, LBP is computed by comparing the magnitude of the center pixel with its neighborhood, as a result, a binary value is assigned to each neighbor pixel. These binary values are converted into decimal value through multiplication by specific weights and addition. This resultant value is known as local binary pattern for that specific window. LBP values are computed for all pixels of image and feature vector histogram is created using histogram binning.

2) Histogram of Oriented Gradients (HOG)

HOG is a widely used feature descriptor in the domain of computer vision [23] [24]. In this work, we extract HOG features for better representation of skin lesion images belong to different classes. To extract HOG features, the segmented image of skin lesion is divided into overlapping blocks. This is followed by computing orientations of gradients from each block. Features are quantized into histogram bins with every bin having a particular range. In the final stage, features from all blocks are combined to form a comprehensive descriptor that represents images from different classes.

3) Bag of Visual Words

Bag of words (BoVW) features descriptor is originally proposed for text document analysis. Recently, it is modified for computer vision applications [25]. Low-level image features of local regions or blocks are used as visual

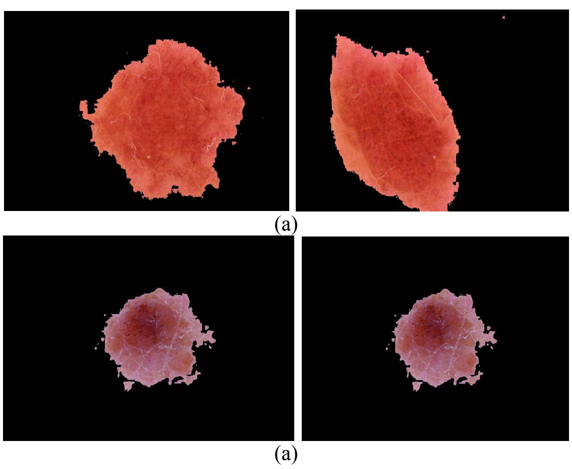

Fig. 3. (a) Segmented images of Benign. (b) Segmented images of Melanoma

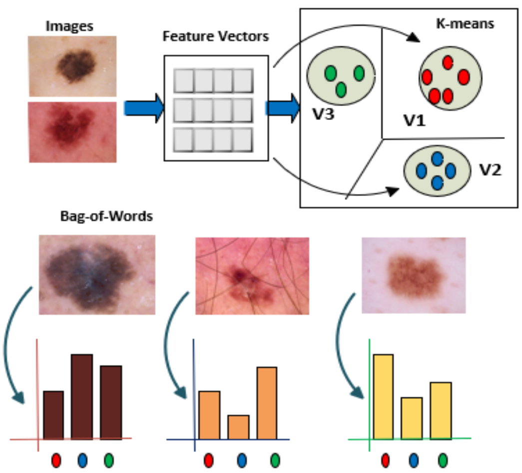

Fig. 4. Scheme of Bag of Visual Words

analogue of word for image analysis. These visual words are clustered through k-means clustering and final descriptor is formed by constructing histograms.

The process of feature extracting from skin lesion image is shown in Fig. 4.

(i) Points/regions of interest are detected in segmented skin lesion images.

(ii) Calculated local feature descriptors around those regions.

(iii) Visual vocabulary is formed by quantization of feature descriptors in words.

(iv) Count the occurrence of each word in image vocabulary for constructing BoVW feature descriptor of desired length.

E. Classification

Skin lesion images were classified through SVM classification method using feature vector extracted in previous stages. SVM is originally proposed for binary problems [17, 26-29]. SVM constructs a hyperplane that performs separation between binary classes using the maximum margin principle. The maximum margin is constructed using only data points which are near to the decision boundary known as support vectors [28-32]. These support vectors provide maximum discriminative information about two classes. Complex classification tasks are effectively handled by SVM by transforming input feature data to higher dimensional space using nonlinear functions known as kernel trick. SVM was originally proposed for two class problem but later on it was modified to tackle multi-class tasks by opting One-vs-One (OVO) or One-vs-All strategies.

In this research, we performed experimentation by choosing SVM as the base classifier. It is also compared with other classifiers such as Decision Tree and K-nearest neighbour.

IV. Results and Discussions

In this research, an automated system for skin lesion detection using dermoscopic images is proposed. The proposed system first preprocesses the raw images using K-means clustering for segmentation of lesion and non-lesion part. Afterward, feature extraction is performed using LBP, HOG, and BoVW feature descriptors. Extensive experimentation is carried out to find the best-representing features and classification methodology. Feature distribution in terms of scatter plot of BoVW features is shown in Fig. 5. It can be observed that the spread of features extracted from melanoma class images is less than that extracted from benign class. Also, clear discrimination among features of both classes advocates the strength of

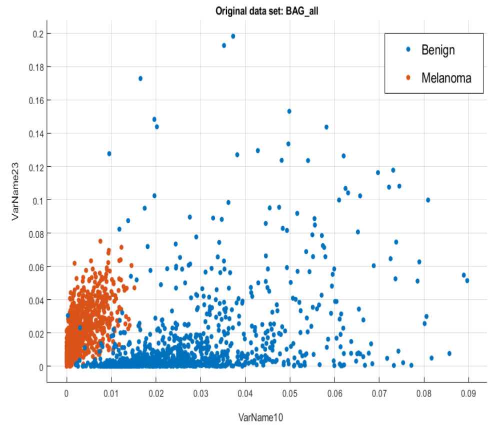

Fig. 5. Scatter Plot of Features

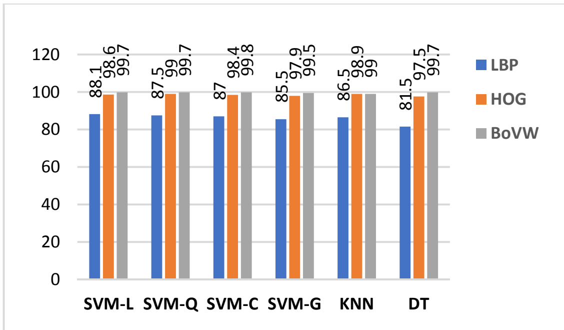

Fig 6. Performance comparison with different classifiers

extracted features, which results in better classification performance.

A comparative analysis is performed among LBP, HOG, and BoVW features with SVM-Linear (SVM-L), SVM-Quadratic (SVM-Q), SVM-Cubic (SVM-C), SVM-Gaussian (SVM-G), KNN with K=10, and Decision Tree (DT) classification methods. All experiments were performed on MATLAB 2019 software and results are averaged over 100 experiments. 5-fold cross-validation (CV) approach was adopted for the evaluation of classification performance. In a 5-fold CV, the whole dataset is divided into 5 groups. Each group is iteratively used for testing while the remaining four are used as training data. In this way, five classifiers are trained iteratively, and the results are an average of five iterations.

Table I. Performance Evaluation over Different Classifiers

Classifiers	Feature sets								
	LBP			HOG			BoVW		
	Acc. (%)	Sen. (%)	Spec. (%)	Acc. (%)	Sen. (%)	Spec. (%)	Acc. (%)	Sen. (%)	Spec. (%)
SVM-L	**88.1**	**100**	**76**	98.6	99	99	99.7	100	99
SVM-Q	87.5	99	76	**99**	**99**	**99**	99.7	99.5	99.5
SVM-C	87	99	75	98.4	99	98	**99.8**	**100**	**99.5**
SVM-G	85.5	95	76	97.9	99	96	99.5	100	99
KNN	86.5	94	79	98.9	99	99	99	100	98
DT	81.5	91	72	97.5	98	97	99.7	99.5	99.2

TABLE II. COMPARATIVE ANALYSIS

Ref.	Year	Method	Accuracy
[1]	2019	Contrast Enhancement	95%
[3]	2018	Gaussian filter for preprocessing Otsu thresholding for segmentation SVM with linear kernel	90.47%
[10]	2018	Geometric Features are extracted KNN Classification	90%
[14]	2019	Deep learning AlexNet, VGG16, ResNet-18	97.55%
[13]	2018	Image Enhancement, Gaussian Filter	82.5 %
[15]	2017	Deep Learning VGGNet CNN	78.66%
[9]	2017	Contour Segmentation followed by texture and color feature extraction	97%
[11]	2016	SVM Classifier Classifier I (Benign or Abnormal) Classifier II (atypical or Melanoma)	Classifier I: 91.5% Classifier II: 93.5%
This work	**2020**	**Classifier: SVM - C Using BoVW**	**99.8%**

The performance of the proposed methodology is evaluated using standard statistical performance matrices such as accuracy (Acc), specificity (Spec), and sensitivity (Sen). Table I presents the comparative performance of various classification methods with LBP, HOG, and BoVW feature sets. It can be observed that BoVW yields maximum classification accuracy of 99.8%, the sensitivity of 100%, and specificity of 99.5% with SVM-C. HOG features also have a comparable performance with the SVM-Q classifier (Table I). HOG and BoVW both feature sets have classification accuracies well above 95% for all six classifiers, this shows the strength and robustness of extracted features.

Table II presents a comparative analysis of recent studies for the same problem. It can be seen that our method has improved the accuracy of the results.

Fig. 6 depicts a graphical comparison of different feature sets used in this study with six classifiers. Fig. 7 shows the classification performance with BoVW features through the SVM-C classification method in terms of the confusion matrix. It can be observed that all 1000 images belong to the benign class were correctly predicted as a

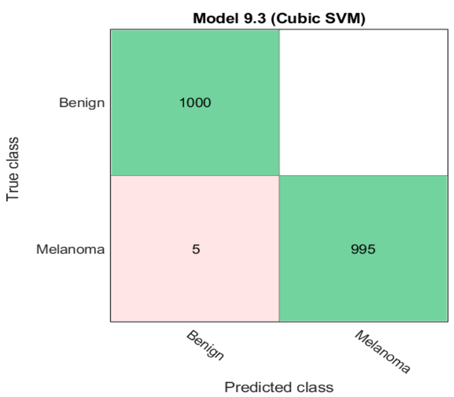

Fig 7. classification performance in terms of confusion matrix

benign class while 5 images belong to the melanoma category were falsely predicted as benign. Fig. 8 provides class wise performance in terms of sensitivity and specificity.

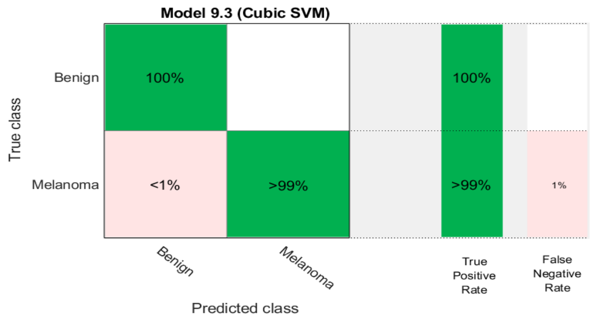

Fig 8. Class-wise performance in terms of sensitivity and specificity

V. CONCLUSIONS

In this research, a novel methodology for the classification of melanoma through dermoscopic images is proposed. The proposed method relies on image segmentation using k-means clustering for the extraction of the region of interest in the image. Feature extraction was performed over a range of feature descriptors namely LBP, HOG, and BoVW. Feature performance was evaluated with different classification methods. The proposed method achieves the best performance of 99.8% mean accuracy through BoVW features with SVM-C classification. The proposed method is reliable and can be effectively used for accurate diagnosis of skin cancer.

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