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# **Bagged Textural and Color Features for Melanoma Skin Cancer Detection in Dermoscopic and Standard Images**

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#### ABSTRACT

Early detection of malignant melanoma skin cancer is crucial for treating the disease and saving lives. Many computerized techniques have been reported in the literature to diagnose and classify the disease with satisfactory skin cancer detection performance. However, reducing the false detection rate is still challenging and preoccupying because false positives trigger the alarm and require intervention by an expert pathologist for further examination and screening. In this paper, an automatic skin cancer diagnosis system that combines different textural and color features is proposed. New textural and color features are used in a bag-of-features approach for efficient and accurate detection. We particularly claim that the Histogram of Gradients (HG) and the Histogram of Lines (HL) are more suitable for the analysis and classification of dermoscopic and standard skin images than the conventional His togram of Oriented Gradient (HOG) and the Histogram of Oriented Lines (HOL), respectively. The HG and HL are bagged separately using a codebook for each and then combined with other bagged color vector angles and Zernike moments to exploit the color information. The overall system has been assessed through intensive experiments using different classifiers on a dermoscopic image dataset and another standard dataset. Experimental results have shown the superiority of the proposed system over state-of-the-art techniques.

**Keywords:** - Malignant melanoma, Skin cancer diagnosis, Dermoscopic images, Standard skin images, Textural and color features.

#### I. INTRODUCTION

In this work, an automatic skin cancer diagnosis system that combines different textural and color features is proposed. New textural and color features are used in a bag-of-features approach for efficient and accurate detection. We particularly claim that the Histogram of Gradients (HG) and the Histogram of Lines (HL) are more suitable for the analysis and classification of dermoscopic and standard skin images than the conventional Histogram of Oriented Gradient (HOG) and the Histogram of Oriented Lines (HOL), respectively. Very recently, three types of features have been used in Existing approaches, namely, geometry features, color features, and finally structural features. More recently, In other approaches adopted asymmetry, border, color and texture features followed by an SVM classifier for the classification of pigmented skin lesions in macroscopic (standard) images. Existing system has some drawbacks such as sensitivity to noise and often results in over segmentation, Not able to reduce dissimilarity and Inefficient

#### **II. RELATEDWORKS**

Barata, Ruela, Mendonca, and Marques (2014) demonstrated, via experi- ments, that color descriptors deliver better performance in detecting melanoma skin lesions than texture descriptors. Barata et al. (2012) adopted a set of directional filters and a connected compo- nent analysis to extract five different features for pigment network detection in dermoscopic images. In Barata, Marques, and Rozeira (2013), the role of key-point sampling in a bag of features ap- proach was investigated. The authors suggested that performance of the system can be influenced by the number of detected key- points. In Barata, Celebi, and Marques (2015), color constancy has been explored to overcome the problem of changes that may occur during the skin image acquisition process. Riaz, Hassan, Javed, and Coimbra (2014) proposed a combination of texture and color features for the classification of melanoma and nonmelanoma skin images. A variation of the local binary patterns (LBP) was used for the texture features to extract scale adaptive patterns. As for the color information, the histograms of the HSV (Hue, Saturation, Value) color space was adopted. More recently, Ruela, Barata, Mar- ques, and

Rozeira (2015) have explored the importance of shape and symmetry features in Melanoma diagnosis in order to deter- mine the type of features that play a crucial role in classification. Abuzaghleh, Barkana, and Faezipour (2015) proposed a combina- tion of Lesion Variation Pattern Features (LVPF) with some ex- tracted shape, color and texture features including the pigment network feature set, the lesion shape feature, the lesion orienta- tion feature, the lesion margin feature, the lesion intensity pattern feature, and the lesion variation pattern feature. In Vasconcelos, Rosado, and Ferreira (2015), color features have been derived from the ABCD rule where the authors proposed a clustering approach to adjust the system to different datasets and image types. In Kruk et al. (2015), different texture and statistical features were adopted, including the numerical descriptors based on the Kolmogorov-Smirnov (KS) statistical distance, the classical Haralick descriptors and fractal texture analysisbased descriptors. In Giotis, Land, Biehl, Jonkman, and Petkov (2015), physician annotations for skin le- sions, referred to as visual diagnostic attributes, were combined with lesion color and lesion texture for melanoma skin detection in non-dermoscopic images. Very recently, three types of features have been used in Chakravorty, Liang, Abedini, and Garnavi (2016), namely, geometry features, color features, and finally structural features. More

recently,Oliveira, Marranghello, Pereira, and Tavares (2016) adopted asymmetry, border, color and texture features fol- lowed by an SVM classifier for the classification of pigmented skin lesions in macroscopic (standard) images.

## III. PROPOSED SYSTEM ARCHITECTURE

In this project, an automatic skin cancer diagnosis system that combines different textural and color features is proposed. New textural and color features are introduced in a bag of features approach for efficient and accurate skin cancer detection. particularly claim that the Histogram of Gradients (HG) and the Histogram of Lines (HL) are more suitable for the analysis Classification of dermoscopic and standard skin images than the conventional Histogram of Oriented Gradient (HOG) and the Histogram of Oriented Lines (HOL), respectively. The use of edge and line orientation in skin images reduces the inter class dissimilarity, and this causes an adversary effect on classification. The HG and HL are bagged separately using a codebook for each and then combined with other bagged Color Vector Angles (CVA) and Zernike moments to exploit the color information.

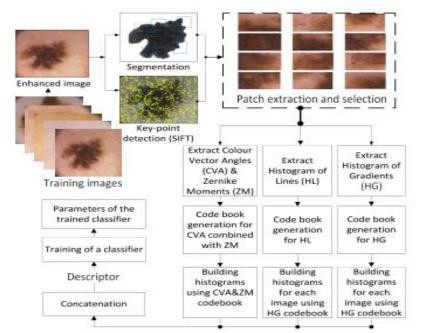


Fig.1 Proposed System Architecture

The following are the functionalities provided by the System: 1. Extract Image

- 2. Data Preprocessing
- 3. Initial key points generalization
- 4. segmentation.
- 5. Train and Test data
- 6. Generate Prediction

7. Log out

The following are the functionalities provided by the User:

1. Get Data set

- 2. Upload Image
- 3. View prediction
- 4. view accuracy result
- 5. View Prediction accuracy ratio

# **IV. RESULTS AND DISCUSSION**

The output screens obtained after executing and running the system are given from Fig.2 to Fig.12

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Fig.2 Checkpoints

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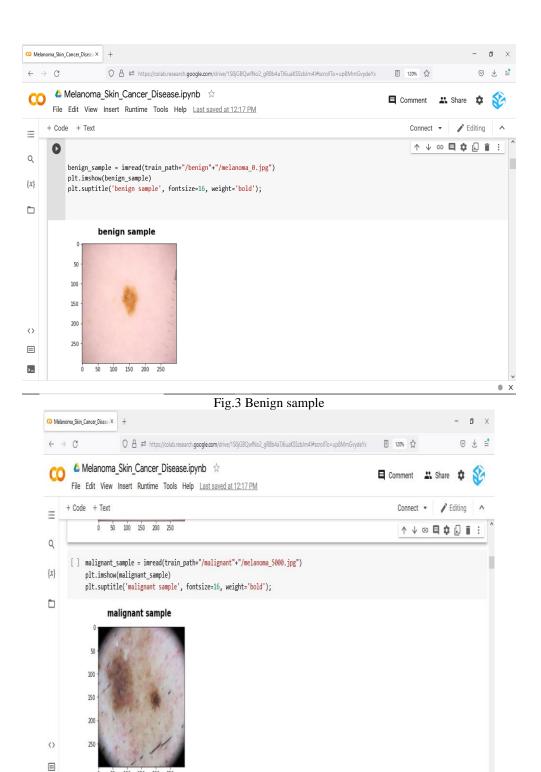


Fig.4 Malignant sample

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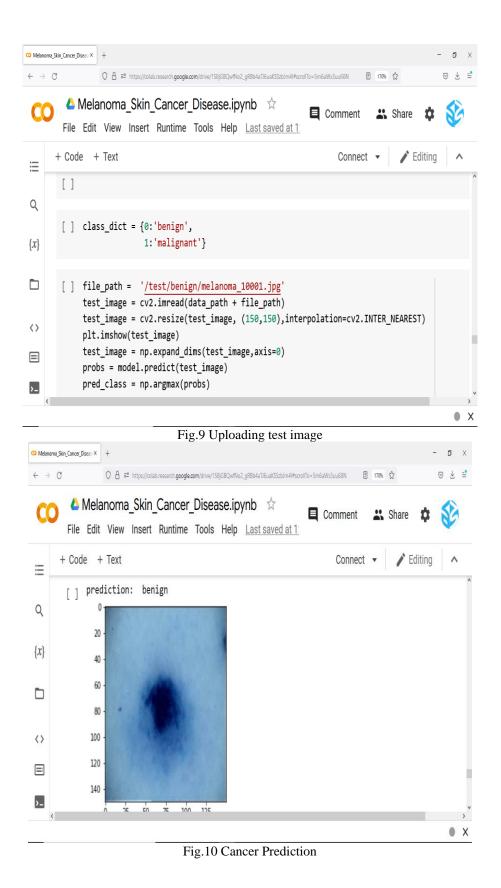
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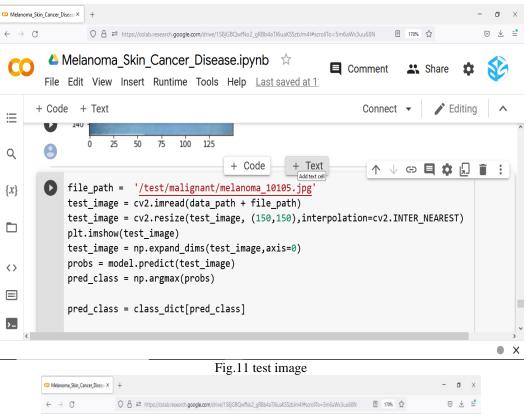
Fig.8 Accuracy graph

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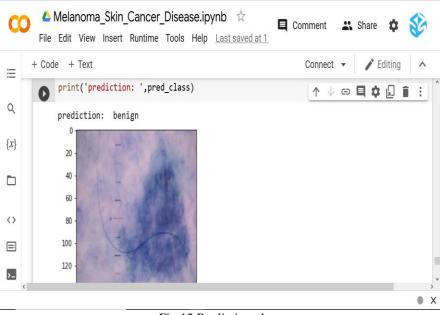


Fig.12 Prediction class

## V. FUTURE SCOPE AND CONCLUSION

In this work, a melanoma skin cancer detection system has been presented. The system relies on a bag of features approach using multiple codebooks are proposed for describing skin cancer lesions efficiently and demonstrated that the orientation information in the conventional histogram reduces the inter class dissimilarity and consequently decreases the discriminative nature of the respective features in skin cancer detection.

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