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Skin Lesion Classification Systems and Dermoscopic Feature Analysis for Melanoma Recognition and Prevention

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***Keywords*-- Skin Cancer, Classification, Neural Network, Computer based detection, Melanoma, Skin Lesion, Image Segmentation, Smart Phone, Android, Wavelet Decomposition, Classifier, Supervised Classification, KNN, Feature Selection, Color Features, Decision Support Systems, Dermatology, Pattern Recognition, Medical Imaging, SVM, Skin Lesion Database, CAD, Shearlet Transform, Multiresolution Analysis Tool, SNE, SSNE, Multi Classifier System, Dermoscopic Images, Image Compression, Image enhancement**

I. INTRODUCTION

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it.

Objective of this study:

This research aims to develop an automatic system to classify the skin lesion images into normal or abnormal images and also the abnormal severity. In the medical field, automated processing and classification of medical images has become an increased need. This demand has led to the development of several techniques to classify the digital Skin cancer images.

The objective of this research are :

a) To identify the significant features needed for the classification of skin lesion images
b) To construct the effective frame work for the skin lesion images calcification
c) To evaluate and compare the proposed methods with the existing methods
d) To train the machine learning algorithm to facilitate effective classification.

Medical imaging is the technique and process of creating visual representations of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues (physiology).

Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat disease.

Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are usually considered part of pathology instead of medical imaging.

II. RELATED RESEARCH CONTRIBUTIONS:

Sforza et. al., Using adaptive thresholding and skewness correction to detect gray areas in melanoma in situ images, (2012) [1] The incidence of melanoma in situ (MIS) is growing significantly. Detection at the MIS stage provides the highest cure rate for melanoma, but reliable detection of MIS with dermoscopy alone is not yet possible. Adjunct dermoscopic instrumentation using digital image analysis may allow more accurate detection of MIS. Gray areas are a critical component of MIS diagnosis, but automatic detection of these areas remains difficult because similar gray areas are also found in benign lesions. This paper explains a adaptive thresholding technique for automatically detecting gray areas specific to MIS. The model uses only MIS dermoscopic images to precisely determine gray area characteristics specific to MIS. To this aim, statistical histogram analysis is employed in multiple color spaces. It is demonstrated that skew deviation due to an asymmetric histogram distorts the color detection process. They introduce a skew estimation technique that enables histogram asymmetry correction facilitating improved adaptive thresholding results. These histogram statistical methods may be extended to detect any local image area defined by histograms.

Garnavi et. al., Computer-aided diagnosis of melanoma using border-and wavelet-based texture analysis (2012) **[2]** The paper presents a computer-aided diagnosis system for melanoma.

The novelty lies in the optimized selection and integration of features derived from textural, border based, and geometrical properties of the melanoma lesion. The texture features are derived from using wavelet-decomposition, the border features are derived from constructing a boundary-series model of the lesion border and analyzing it in spatial and frequency domains, and the geometry features are derived from shape indexes. The optimized selection of features is achieved by using the gain-ratio method, which is shown to be computationally efficient for melanoma diagnosis application. Classification is done through the use of four classifiers; namely, support vector machine, random forest, logistic model tree, and hidden naive Bayes. Other important findings include 1) the clear advantage gained in complementing texture with border and geometry features, compared to using texture information only, and 2) higher contribution of texture features than border-based features in the optimized feature set**.**

Sigurdsson et. al., Detection of skin cancer by classification of Raman spectra (2014) [3]. Skin lesion classification based on in vitro Raman spectroscopy is approached using a nonlinear neural network classifier. The classification framework is probabilistic and highly automated. The framework includes a feature extraction for Raman spectra and a fully adaptive and robust feed forward neural network classifier. Moreover, classification rules learned by the neural network may be extracted and evaluated for reproducibility, making it possible to explain the class assignment. Small distinctive bands in the spectrum, corresponding to specific lipids and proteins, are shown to hold the discriminating information which the network uses to diagnose skin lesions.

Lequan, Y. U et. al., Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks (2016)[4] Automated melanoma recognition in dermoscopy images is a very challenging task due to the low contrast of skin lesions, the huge intraclass variation of melanomas, the high degree of visual similarity between melanoma and non-melanoma lesions, and the existence of many artifacts in the image. In order to meet these challenges, They used a method for melanoma recognition by leveraging very deep convolutional neural networks (CNNs). Compared with existing methods employing either low-level hand-crafted features or CNNs with shallower architectures, our substantially deeper networks (more than 50 layers) can acquire richer and more discriminative features for more accurate recognition. To take full advantage of very deep networks, They propose a set of schemes to ensure effective training and learning under limited training data.

First, They apply the residual learning to cope with the degradation and overfitting problems when a network goes deeper. The technique can ensure that our networks benefit from the performance gains achieved by increasing network depth. Then, They construct a fully convolutional residual network (FCRN) for accurate skin lesion segmentation, and further enhance its capability by incorporating a multi-scale contextual information integration scheme. Finally, They seamlessly integrate the FCRN (for segmentation) and other very deep residual networks (for classification) to form a two-stage framework. This framework enables the classification network to extract more representative and specific features based on segmented results instead of the whole dermoscopy images, further alleviating the insufficiency of training data. This study corroborates that very deep CNNs with effective training mechanisms can be employed to solve complicated medical image analysis tasks, even with limited training data.

Xie, F. Y et.al., Melanoma classification on dermoscopy images using a neural network ensemble model (2016) [5]The algorithm follows three steps: first, lesions are extracted using a self-generating neural network (SGNN); second, features descriptive of tumor color, texture and border are extracted; and third, lesion objects are classified using a classifier based on a neural network ensemble model. In clinical situations, lesions occur that are too large to be entirely contained within the dermoscopy image. To deal with this difficult presentation, new border features are proposed, which are able to effectively characterize border irregularities on both complete lesions and incomplete lesions. In our model, a network ensemble classifier is designed that combines back propagation (BP) neural networks with fuzzy neural networks to achieve improved performance.

Kosapan, P et. al., Empirical mode decomposition of blood flow data for melanoma classification (2016) [6] Blood flow signals can characterize a notable feature correlating to melanoma, the most serious type of skin cancer. In this study, blood flow signals are decomposed into their instituent components in terms of intrinsic mode functions (IMFs) using the empirical mode decomposition (EMD). In particular, only the first two IMF components of blood flow signals are examined. The blood flow data analyzed were recorded from four different lesions (melanoma, psoriasis, benign atypical nevi, and benign typical nevi) using laser Doppler flowmetry (LDF). The root mean square (RMS) of IMF components of blood flow signals is used a quantitative feature for melanoma classification.

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From the computational results, it is shown that there are significant differences between the RMS values of IMF components of blood flow signals recorded from the melanoma lesion and those recorded from other lesions. Furthermore, the computational results suggest that overall the first IMF components of blood flow signals provide a better performance on melanoma classification.

Sagar, C et. al., Color channel based segmentation of skin lesion from clinical images for the detection of melanoma (2016) [7] A simple and efficient method for the automatic segmentation of c1inical images using color space analysis and improved binary thresholding algorithm is used. C1inical images taken from normal mobile cameras have the inherent problem of improperly illumined background compared to dermoscopic images. This algorithm corrects these constraints with initial pre-processing steps of adjustments of c1inical image. The efficiency of the overall segmentation process is carried out by calculation of similarity matrices for segmented lesions from each color channel used.

Joseph, S et. al Skin lesion analysis system for melanoma detection with an effective hair segmentation method (2016) [8] A benign skin lesion is a normal skin, atypical skin lesion may or may not be cancerous and melanoma is surely a cancerous one. This paper uses a non invasive automated skin lesion analysis system for the early detection of melanoma using image processing techniques and mobile technologies. Hair detection and removal is performed for effective classification and extraction features of the skin wound. A fast marching in painting algorithm is used for the hair removal.

Jamil, U et. al., Dermoscopic feature analysis for melanoma recognition and prevention (2016) [9] The full model of an automated system includes three important stages in order to comply with the lesion analysis: segmentation, feature extraction and classification. The data-set contains images and annotations provided by physicians. Segmentation is an imperative preprocessing step for CAD system of skin lesions. Feature extraction of segmented skin lesions is a pivotal step for implementing accurate decision support systems. Dermatologists take keen interest in examining a specific clinically significant part in a lesion. That part is projected to have lesion information in the form of texture that can be relevant for detection. In case of detection of melanoma various local features for example pigment network and streaks usually occur in peripheral region of the lesion. This led to the extraction of peripheral part for feature extraction instead of whole lesion processing.

Afifi, S et. al., A low-cost FPGA-based SVM classifier for melanoma detection (2016) [10] This study aims to develop a real-time embedded classifier to be implemented on a low-cost handheld device dedicated for early detection of melanoma. Melanoma is the most dangerous form of skin cancer, which is responsible for the majority of skin cancer related deaths. Therefore, this device would be very beneficial in the primary care. In this paper, a hardware design is used to implement a linear binary SVM classifier in an FPGA targeting online melanoma classification. A recent hybrid Zynq platform is used for the implementation of this system designed using the latest High Level Synthesis design methodology. The implemented system demonstrates high performance, low hardware resources utilization and low power consumption that meet vital embedded systems constraints.

Satheesha, T. Y et. al., Melanoma Is Skin Deep: A 3D Reconstruction Technique for Computerized Dermoscopic Skin Lesion Classification (2017) [11] This paper introduces a non-invasive computerized dermoscopy system that considers the estimated depth of skin lesions for diagnosis. A 3D skin lesion reconstruction technique using the estimated depth obtained from regular dermoscopic images is presented. On basis of the 3D reconstruction, depth and 3D shape features are extracted. In addition to 3D features, regular color, texture and 2D shape features are also extracted. Apart from melanoma, in-situ melanoma this system is designed to diagnose basal cell carcinoma, blue nevus, dermatofibroma, haemangioma, seborrhoeic keratosis and normal mole lesions. Different feature set combinations is considered and performance is evaluated.

Yoshida, T et. al., Simple and effective pre-processing for automated melanoma discrimination based on cytological findings (2016) [12] In this paper, a simple and effective preprocessing method for melanoma classification by considering cytological properties of melanomas, in particular the alignment of the major axis of the tumor in the same direction is presented. They evaluate our method with a set of 1,760 dermoscopic images (329 of melanomas and 1,431 of nevi) and a simple convolutional neural network (CNN) classifier with five-fold cross validation. This tumor alignment method improves the classification performance**.**

Soumya, R. S et. al., Advanced earlier melanoma detection algorithm using colour correlogram (2016) [13] Now most of the existing skin lesion analysis system use ABCDE parameters for feature extraction. But these methods have lot of drawbacks.

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In this paper an advance earlier melanoma detection algorithm has done using colour correlogram and texture analysis. Bayesian classifier is used to detect the abnormal skin cells with colour correlogram and SFTA feature vectors**.**

Takruri, M et. al., Multi-classifier decision fusion for enhancing melanoma recognition accuracy (2016) [14] this paper uses an automated non-invasive multi-classifier system for skin cancer (melanoma) detection. This system fuses the results obtained from three classification systems to enhance the melanoma detection rate. All of the classification systems use Support Vector Machine classifier. However, the image feature sets used in each classification system are different. The features sets used are Wavelets and Color features, Curvelets features and Grey Level Co-occurrence Matrices features. The output class labels or class probabilities of the three classification systems are combined using Majority Voting or Averaging Fusion to obtain enhanced classification rates. The dataset used include digital images for benign and malignant skin lesions**.**

Yao, T et. al., A Multiview Joint Sparse Representation with Discriminative Dictionary for Melanoma Detection (2016) [15] In this paper, the representation of lesions is formulated as a multiview joint reconstruction problem with the learned dictionary. To better characterize the lesion images, a special common dictionary learning method is used which explicitly takes both shared common pattern and a set of class specific patterns between melanomas and nevi into account. In addition, group sparsity and locality constraints are further integrated to preserve the relationship and structure among local features. Furthermore, in order to enhance the combination capability of multiview, the spare coefficients of multiple features are jointly learned in a unified framework.

Yuan, X et. al., SVM-based texture classification and application to early melanoma detection (2006) [16] In this paper, exploration of texture information, one of the criteria dermatologists use in the diagnosis of skin cancer, but has been found very difficult to utilize in an automatic manner was done. The overarching goal is to improve the overall decision support capability of the DSS. The objective is to use texture information ONLY to classify the benign and malignancy of the skin lesion. A three-layer mechanism that inherent to the support vector machine (SVM) methodology is employed to improve the generalization error rate and the computational efficiency. The performance of the algorithm is validated with a series of benchmark texture images and then tested on 22 pairs of real clinical skin lesion images.

Moussa, R et.al., Computer-aided detection of Melanoma using geometric features (2016) [17] Melanoma is one type of skin cancer that usually develops from prolonged exposure to UV light. The latter triggers mutations that lead skin cells to multiply rapidly and form malignant tumors. If not cured, Melanoma can result in one's death. Hence, an early detection of this deadly cancer is important to prevent it. Certain lesion characteristics such as Asymmetry, Border, Color and Diameter segmentation (ABCD rule), can indicate the presence of Melanoma. In this work, the use of geometric features to differentiate between a benign lesion and a malignant one was investigated. The k-Nearest Neighbors (k-NN) machine learning algorithm is used to classify 15 lesions based on their ABD features.

Tsapras, A et. al., Hyperspectral imaging and spectral classification for assisting in vivo diagnosis of melanoma precursors: preliminary results obtained from mice (2016) [18] Early detection of signs of skin dysplasias at their curable stage is crucial. Here present an integrated system combining a Hyper spectral Camera system (HyCam), with spectral classification algorithms, developed for the in vivo and objective discrimination between non dysplastic, dysplastic nevi and melanomas. A melanoma animal model was developed in order to monitor the process of melanoma development. Reference spectra were collected from normal skin areas, which were compared with the spectra obtained from the lesions using the Spectral Angle Mapper (SAM) algorithm. A pseoudocolor map was created with different colors representing various degrees of similarity between test and reference spectra. The system's predictions ware validated with biopsy/histology.

Roh, M. R et. al., Cutaneous melanoma in women",International Journal of Women's Dermatology (2017) [19] The gender-linked physiologic differences in skin and melanoma are addresed. The influence of estrogen on a woman's risk for melanoma and melanoma outcomes with regard to pregnancy, oral contraceptives, hormone replacement therapy, and UV tanning. The findings on gender disparities inmelanoma have yielded many advances in our understanding of this disease. Biological, environmental, and behavioral factors may explain the observed gender difference inmelanoma incidence and outcome. Further research will enable us to learn more about melanoma pathogenesis, with the goal of offering better treatments and preventative advice to our patients.

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Bi, L., Kim, J et al.,. "Automatic melanoma detection via multi-scale lesion-biased representation and joint reverse classification (2016) [20] Existing methods however have problems in representing and differentiating skin lesions due to high degree of similarities between melanoma and non-melanoma images and large variations inherited from skin lesion images. To overcome these limitations, this study uses a automatic melanoma detection method for dermoscopy images via multi-scale lesion-biased representation (MLR) and joint reverse classification (JRC). This MLR representation enable us to represent skin lesions using multiple closely related histograms derived from different rotations and scales while traditional methods can only represent skin lesion using a single-scale histogram. The MLR representation was then used with JRC for melanoma detection. This JRC model allows us to use a set of closely related histograms to derive additional information for melanoma detection, where existing methods mainly rely on histogram itself.

III. Proposed Research Work

The performance of the proposed system is analyzed using PH^2 database. It contains a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. All images are 8-bit RGB color images with a resolution of 768x560 pixels. The classification performance is measured as the percentage of test set images classified into the correct skin lesion class. Also, sensitivity and specificity measures are computed for the analysis.

In this work, an efficient skin lesion classification system based on Multi Resolution Analysis (MRA) is proposed. Discrete Shearlet Transform (DST) is a MRA tool that has been applied to various image processing problems. It is a multi resolution and multi directional analysis tool.

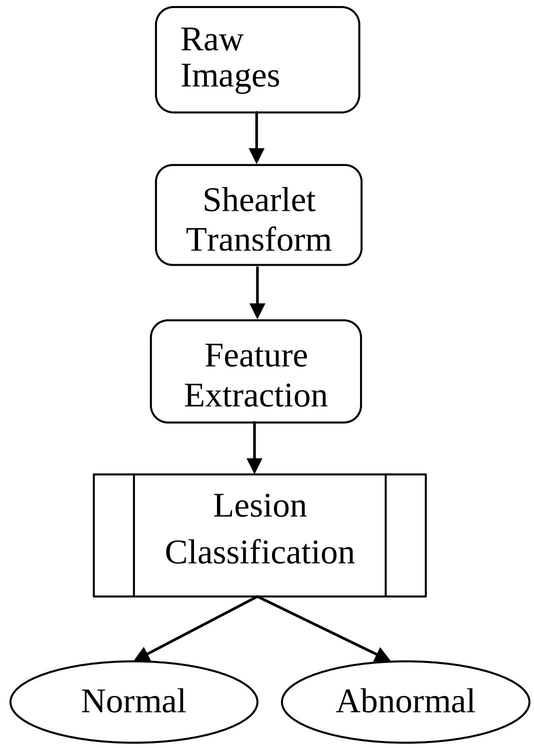

Fig. 1: Block Diagram of Proposed Skin Classification System

The proposed system for the classification of skin lesion mainly consists of two different stages. They are feature extraction and classification. In the feature extraction stage the training dermoscopic images are decomposed by using DST at given resolution level. The energy of shearlet coefficients of all the directional sub bands is computed and these energy values are considered as features for the classification process. This method is applied to all the training dermoscopic images and the calculated feature vectors are stored in the database.

This feature database is used as one of the input to the classification phase. In the classification stage, Support Vector Machine (SVM) is used. The main advantages of SVM are its fast convergence rate and superior generality in high dimensional data.

IV. Tools And Methods, Techniques Proposed

The new proposed framework for the classification of skin lesion images based on Discrete Wavelet Transform (DWT), Stochastic Neighborhood Embedding (SNE) and Symmetric SNE (SSNE) and Support Vector Machine (SVM) is proposed. This paper focuses more on literature survey observation presentation.

V. Training And Testing Databases

The performance of the proposed system is analyzed using PH^2 database. It contains a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. All images are 8-bit RGB color images with a resolution of 768x560 pixels. The classification performance is measured as the percentage of test set images classified into the correct skin lesion class. Also, sensitivity and specificity measures are computed for the analysis

VI. Conclusion

Automatic diagnosis of skin cancer is feasible and achievable through the usage of well-defined segmentation and classification technique. While many successes has been recorded in the current advances in automation of medical diagnosis, this study tends to maximize the large availability skin cancer diagnosis, image set towards providing cost-effective, easier and faster diagnosis for underserved areas.

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