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Robust Skin lesion Classification via Machine Intelligence

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Abstract: ***Skin cancer is typically growth and spread of cells or lesion on the uppermost part or layer of skin known as the epidermis. It is one of rarest and deadliest found type of cancer, if undetected or untreated at early stages may lead in patient's demise. Dermatologists use dermatoscopic images to identify the type of skin cancer by identification of asymmetry, border, colour, texture & size mole or a lesion. This method of detection can also be applied using machine learning techniques for classification these images into respective of cancer. There have been various studies and techniques which have been proposed various researchers across the globe in order to improve the classification of these dermatoscopic images. The proposed studies primarily focus on classification of dermatoscopic images based on lesion's colour and texture features followed by intelligent machine learning approaches. Advances in these machine intelligent approaches such as deep neural networks and convolutional neural networks can be applied on dermatoscopic images to identify their features. A CNN based approach provides a additional accuracy over feature extraction as the algorithm is applied on pixel in overall image size. CNN also provides the ability to perform huge chunk of mathematical operations which is basic requirement in case of image processing and machine learning. The CNN based algorithm can be used to classify the dermatoscopic images with better efficiency and overall accuracy with having power of artificial-neural-network.***

Keywords: ***Artificial Intelligence, Computer Vision, Deep Learning, Image Classification, Skin lesion classification.***

I. INTRODUCTION

Skin cancer is abnormal growth of cells in the epidermis caused by deoxyribonucleic acid (DNA) damage. These lead the skin cells to multiply rapidly and form malignant tissues. The main types of skin cancer are basal cell carcinoma, melanoma and dermatofibroma. The main cause of skin cancer is the exposure to ultraviolet rays via naturally or working on artificial machine. Skin cancers aren't all identical, and they may not cause many symptoms.

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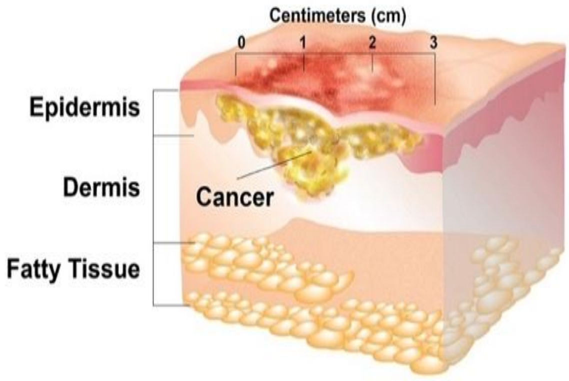

Fig-1: Skin cancer [27]

Each year, about 91,000 people are diagnosed with melanoma, and more than 9,000 people die from it. Rates of melanoma are on the rise, especially among children and teens. If un-treated at early stages may cause death of patients. In 2018, the American Cancer Society estimates 9,000 Californians will be diagnosed with melanoma, the most of any state [28]. Melanoma is more frequently diagnosed in non-Hispanic whites. 74 percent of melanoma cases occurred among Indian citizens aging 50 and older during period of 2008-12. Women are more likely to be diagnosed with melanoma than men during their lifetimes. However, at the age of 65, men are diagnosed with melanoma at double the rate of women and at the age of 80, the chances of melanoma detection in men is three times more than women of same age. [26]

II. HAM10000 DATASET [25]

HAM literally meaning Human Against Machine is the dermatoscopy dataset created to solve the question of availability of data diversification in dermatoscopy. The dataset is a huge collection of 10015 pigmented skin images of seven different types. The dataset is acquired from collection of lesions identified by clinical experts by various methods of dermatology image analysis. The dataset is acquired by considering samples from different age groups and gender. This huge and diversified dataset of dermatology is acquired and stored with help of various modalities. The dataset was also used as the training dataset for ISIC-2018 challenge hosted by International skin imaging collaboration.

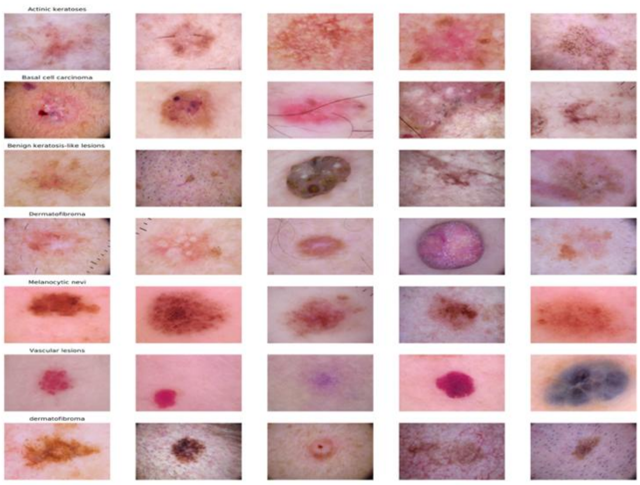

Fig-2: HAM10000 Dataset Samples [25]

III. LITERATURE SURVEY

Various researchers have proposed the machine learning algorithms and approaches for classification of these images which include techniques like CNN, SVM, RNN for classification. These studies also used various feature extraction like otsu's automatic thresholding and snake contour detection model to extract the required features from images. Suleiman Mustafa et al. [1] proposed a SVM algorithm for classification of melanoma using RGB colour and texture of skin lesion to classify it. Nazia et al.[2] Used deep CNN to train the model and then classifying it via SVM to detection of skin cancer using color and texture features. Soniya et al. [3] extracted various features such as color and texture from segmented lesion region for skin lesion detection using otsu thresholding method. Zahara et al. [4] Proposed an HSV based color extraction and GLSM based texture feature extraction of dermatoscopy images with SVM classifier to classify the type of cancer. Prachaya et al. [5] Proposed a snake (a contour) detection based model with SVM classifier to classify skin cancer. R S Soumya [6] Used colour correlogram for extracting colour features of the melanoma. The system also uses contour-based image segmentation of images and classifying the images based on Basian classifier. S Jain et al. [7] Used combined output of otsu thresholding and binary masking for feature extraction from images and the classifying images to melanoma or normal skin mole. Lei Bi et al [9] Used joint reverse classification (JRC) to classify images based on colour features. Catarina Barata et al. [10] Proposed colour constancy model for extraction of colour features of melanoma and classification of images with various machine learning algorithms like KNN, SVM (RBF Kernel), Adaboost etc. Ze Ma et al. [11] Proposed a deep attenuation network (DAN) with colour constancy model to improve classification of the dermatoscopic images. NCF Codella et al. [12] stated an ensemble learning approach for classification and achieved a good accuracy score of 0.77 for classification. Rashika Mishra et al [13] worked on a deep machine learning model based on CNN for skin lesion segmentation with good classifier results. Gerad Schaefer et al [14] worked on detection of image segmentation based on JSEG automatic border detection principles and applying ensemble learning approach for achieving a good classification accuracy of 93.83%. Nikhil Cheerla et al. [15] proposed multi-stage neural network for classification of images for data acquired from PH-2 dataset for dermatoscopy. Jorye Marques et al [16] proposed image classification based on colour and texture with high sensitivity of 94%. Frahan riaz et al. [17] proposed a local binary patterns algorithm with RGB and HSV colour histograms for achieving good sensitivity 84% and 83% respectively. Dr. J Abdul Jaleel et al [18] proposed an ANN (Artificial neural network) based system for classification with 2-D wavelet transform for feature extraction from images. Hitoshi Iyatomi et al. [19] worked on a system-based ANN for image classification on collection of images from three different datasets for identification of melanoma. Herad Gangster et al. [20] proposed automated system for melanoma recognition with K-Nearest neighbor with sensitivity of 87% as performance metrics. G D leo et al. [21] designed a software tool for melanoma identification with sensitivity of 83% for a system trained on collection 300 images. G D Leo et al. [22] proposed algorithm based on Decision tree (C4.5) machine learning algorithm with both specificity and sensitivity both more than 85%. Ning Situ et al [24] worked on developing classifier model using Naïve Bayes and SVM. with max AUC of 82.21%. Yunus Fazilogl u et al worked on feature extraction of dermatoscopic images using colour histogram method.

Authors	Techniques	Dataset	Performance Metrics
Suleiman Mustafa et al. [1]	SVM (RBF) Kernel	Dermis & DermQuest	86.67%
Nazia Hameed et al [2].	CNN & SVM	PH2, Dermis, DermQuest	86.2%
Soniya Mane et al. [3]	SVM Linear & RBF	PH2	Linear- 92.3% & RBF - 88.46%
Zahra Waheed et al.[4]	SVM	PH2	96%
Soumya R S et al. [6]	Basian	PH2	91.5%
Lei Bi et al. [9]	Joint Reverse Classification	PH2	92%
Catarina Barata et al. [10]	Colour Constancy	PH2(30 images)	81.7%
Ze Ma et al. [11]	Colour Constancy	ISIC	AUC: 76.3% - None 78.7% - Max RGB 79.4% - Shades of Grey 78.3 % Grey edge

N. C. F. Codella et al. [12]	CNN	ISIC, ISBI	Acuracy: 77%
Rashika Mishra et al. [13]	CNN	ISBI-2017	Accuracy: 92.8% Jeccard Index: 0.842
Gerald Schaefer et al. [14]	Ensemble learning with JSEG auto border detection	Collection of 564 images	Accuracy: 93.83%
Nikhil Cheerla et al.[15]	Multi- stage neural network	PH2	Single stage: 95% Hierarchical classification: 98.9% Chained classification: 95.2%
Jorge S. Marques et al.[16]	Binary classifier	Collection of images provided by Hospital Pedro Hispano	SE: 94 % SP: 77.4%
Farhan Riaz et al.[17]	LBP	Collection of 200 dermatoscop y images	SE: LBP +HSV: 84% LBP+RGB: 83% SP: LBP +HSV: 94% LBP+RGB: 88%
Dr. J. Abdul Jaleel, et al. [18]	ANN (Back propogation) with 2D wavelet transform for feature extraction	Collection of images from various sources	N/A
Hitoshi Iyatomi, et al. [19]	ANN	Collection of total 1268 images different datasets	SE:85.9% AUC: 92.8% SP: 86.0%
Harald Ganster wt al. [20]	KNN	Images from Vienna General Hospital	SE:87% SP:92%
G. Di Leo et al.[22]	C4.5 Decision Tree	Collection of 173 images	SP: >85% SE: >85%
M. Emre Celebi et al. [23]	SVM	Collection of 564 images	SP: 92.34% SE: 93.33%
Ning Situ et al.[24]	SVM	Collection of 100 images	AUC: 82.21%

Table 1: Summary of Prominent Literature

IV. CHALLENGES IN IDENTIFICATION OF SKIN CANCER

Dermatoscopy is a clinical diagnosis technique which uses skin reflections to produce images of skin legions, these images are furthered analyzed by trained and experienced physicians (mainly Dermatologists) to distinguish images in identification of skin cancer, especially melanoma. As per studies over years in field of dermatology and machine learning most of the researchers used SVM machine learning technique to categorize the images based on features extracted from the dataset. In spite of having good accuracy score for previously proposed methods it is difficult to conclude the efficiency of the proposed algorithms on real world data. Most popular dataset available for researchers is PH2 Dermatoscopy dataset, which is limited to set of 200 images which is very small amount of data considering the domain of Healthcare. With advancements in deep learning image analysis techniques and availability of data new techniques can be implemented which have more computational accuracy and precision.

V. PROPOSED SYSTEM

As discussed earlier, we propose a deep machine learning model for categorization of dematoscopic images. We propose the CNN based approach for feature extraction from the images. A 2-dimentional convolution can be applied on the array of dermatoscopic images to efficiently extracting the features from the images. The model will be given the input of transformed images by adjusting contrast, brightness and zoom level on the image for targeting the skin lesions in images. We will also monitor changes in model performance metrics-based changes in hyper parameters of the proposed CNN architecture, in order to effectively select optimal values for the training of network with maximum efficiency and reducing chances of overfitting the model. We are also planning to compare our results with standard and proven deep image learning models for comparison and checking accuracy of our model. The image shows high level approach for designing a CNN based model for dermatology image classification.

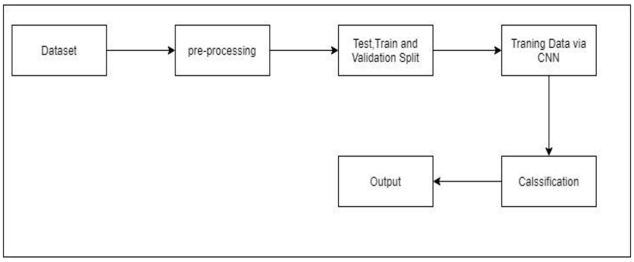

Fig: 3 Proposed System Architecture.

As shown in Figure 3 we will use HAM10000 dermatology dataset, and then apply image transformation on the image sets by adjusting contrast, brightness. As a part of pre-processing technique, we will also apply image rotations and zooming on images to focus only the pigmented section of the image. After acquiring data and after completion of pre-processing we will split the data set using standard method for splitting data into test, train and validation sets. In the training phase we use train data from split to generate inferences from data using 2-dimentional convolution layer which will also generate feature sets for the type of images.

After feature set extraction, inferences from the image data will be forwarded to the fully connected layer pf CNN which does classification of image from the trained model and inferences. The network will generate the output of image as the class of skin cancer it belongs to.

VI. Results

As described in proposed architecture we worked on building CNN (convolutional neural network) based deep learning models to classify these pigmented skin images. As part our analysis we worked on AlexNET [29] and ResNET [30] based models for classification of images.
These models are trained on processed images after adjusting brightness, rotation and random zoom on images. Accuracy metrics for both models is shown below table.

Table 2. Result Analysis

Model	Epochs	Accuracy
AlexNET	50	77.13%
ResNET-18	50	82.57%

VII. Conclusion

Melanoma skin cancer is one of the rarest and fatal type of cancer known today, if untreated at primary stage may result in death of patient. Skin lesion can be easily identified from its shape, size, colour and texture similar techniques can be applied in computer programs for identification of skin lesion types. Increasing risks of skin cancer is leading to increase in mortality rate due to unavailability of medical facilities and shortage of Dermatology specialist. Machine learning solution for identification of the skin cancer can help doctors to take necessary action in order to take care of patient's health. We have achieved over 82% accuracy in our experiment for classification of images using ResNET-18 [30] architecture.ResNET-18 based architecture improves overall accuracy in all classes of images in HAM1000 dataset. Deep learning is most promising solution which improves overall accuracy of classification and the system will complement the Doctor's decision.

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