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ADVANCED SKIN DISEASE DIAGNOSIS USING IMAGE PROCESSING

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ABSTRACT:

Malignant melanoma is the deadliest form of skin cancer. Dermoscopy is a noninvasive high-resolution imaging technique that assists physicians for more accurate diagnoses of skin cancers. Melanoma is a fast-growing aggressive type of skin cancer. Due to this feature, malignant melanoma remains one of the fastest growing cancers worldwide. After it metastasizes from its origin into other tissues, the response rate to treatment declines as low as 5%, and its 10-year survival rate is only about 10% After it metastasizes, there is no surgical rem detection of malignant melanoma is critically important. Among many types of skin cancers, melanoma has the highest false negative ratio.Therefore, this thesis proposes three methods for early detection of malignant melanoma. More specifically, this thesis,Introduces a novel approach of texture-based abrupt cutoff quantification method . In current clinical practice, abrupt cutoff evaluation is subjective and error-prone. In our method, we introduce a novel approach to objectively and quantitatively measure abrupt cutoff.To achieve this, we quantitatively analyzed the texture features of a region within the skin lesion boundary using level set propagation (LSP) method.Then, we built feature vectors of homogeneity, standard deviation of pixel values, and mean of the pixel values of the region of interest between the contracted border and the original border of a skin lesion. These vectors were then classified using neural networks (NN) and support vector machines (SVM) classifiers.

Keyword:

Deep Learning,Transfer Learning,Malignant,Melenoma,

INTRODUCTION:

The occurrence of malignant melanoma, which is the deadliest form of skin cancers, has been elevated in the last decade. Between 2009 and 2010, the mortality rate due to melanoma increased by 3% in the USA.Skin cancer occurrence has become more common not only in the USA but also in different countries with Caucasian people majority such as the UK and Canada with 10,000 diagnoses and annual mortality of 1,250 people.Early diagnosis of the melanoma has been spotlighted due to the persistent elevation of the number of incidents, the high medical cost, and increased death rate.

Dermoscopy, which is one of the noninvasive skin imaging techniques, has become a key method in the diagnosis of melanoma. Dermoscopy is the method that magnifies the region of interest (ROI) optically and takes digital pictures of the ROI.Misdiagnosis or under diagnosis of melanoma is the main reason for skin cancer-related fatalities.The cause of these errors is usually due to the complexity of the subsurface structures and the subjectivity of visual interpretations.

Expert clinicians look for the presence of exclusive visual features to diagnose skin lesions correctly in almost all of the clinical dermoscopy methods. These features are evaluated for irregularities and malignancy.However, in the case of an inexperienced dermatologist, diagnosis of melanoma can be very challenging.

The problems addressed in this thesis are; how to eliminate the subjectivity on visual interpretation of dermoscopy images for border irregularity/abruptness; how to improve the performance of feature extraction algorithms by providing more accurate skin lesion segmentation; and how to reduce the number of false-negative diagnosis.

Images used in this thesis are obtained from the International Skin Imaging Collaborations Archive.

OVERVIEW OF MACHINE LEARNING:

Machine learning (ML) is an area that aims to construct new algorithms to make predictions based on given data. ML generates general models using training data so that these models can detect the presence or the absence of a pattern in test (new) data.Patterns can be a low-level or a high-level.

Biological neural network is an important part of the human brain. It is a highly complex system and has an ability to process different tasks simultaneously. Neural network (NN) is a classifier that simulates the human brain and neurons.Instead of neurons, “perceptron” is used as a basic unit of NN .NN architecture consists of the different layers .

The back-propagation algorithm can be divided into two phases: propagation and weight update. In the first phase of this algorithm, an input vector is propagated forward through the neural network, and the output value is generated

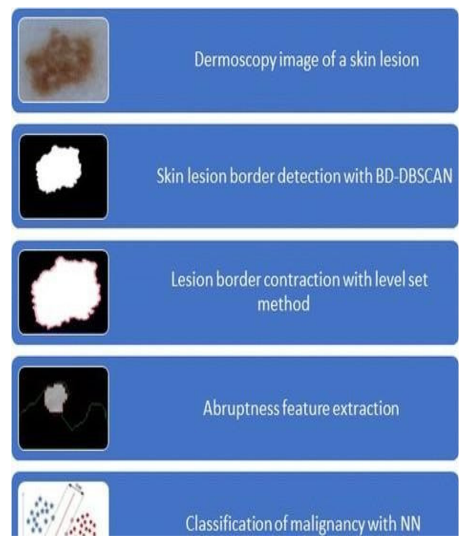
DEEP LEARNING AND TRANSFER LEARNING:

Deep learning, also known as Deep Structured Learning, is a subdivision of ML supported by mass of algorithms.Deep learning can extract useful features directly from images, text and sound in supervised and/or unsupervised manners which makes it different than standard machine learning techniques.. In fact, feature extraction with this approach is considered as a part of the learning process. Transfer learning is a ML technique where a model that is trained on one task is repurposed on another related task.

Abruptness of pigment patterns at the periphery of a skin lesion is one of themost important dermoscopic features for detection of malignancy.In the current clinical setting, abrupt cutoff of a skin lesion is determined by an examination performed by a dermatologist.

This region was bounded by an interior border line of the lesion boundary which is determined using level set propagation (LSP) method.This method provides a fast border contraction without a need for extensive boolean operations.Then, we built feature vectors of homogeneity, standard deviation of pixel values, and mean of the pixel values of the region between the contracted border and the original border.

The data set for this part of the thesis was obtained from ISIC 2016: Skin Lesion Analysis Toward Melanoma Detection [59], which has 900 dermoscopic images with 727 benign and 173 malignant lesions, and Edra Interactive Atlas of Dermoscopy [60], which has 73 benign and 27 malignant lesions.



[3] discussed that In surgical planning and cancer treatment, it is crucial to segment and measure a liver tumor's volume accurately. Because it would involve automation, standardisation, and the incorporation of complete volumetric information, accurate automatic liver tumor segmentation would substantially affect the processes for therapy planning and follow-up reporting. Based on the Hidden Markov random field, Automatic liver tumor detection in CT scans is possible using hidden Markov random fields (HMRF-EM).

Then, we considered the offset of a continuous function of whole lesion border via constant velocity level sets and contracted the lesion border using these levelsets.

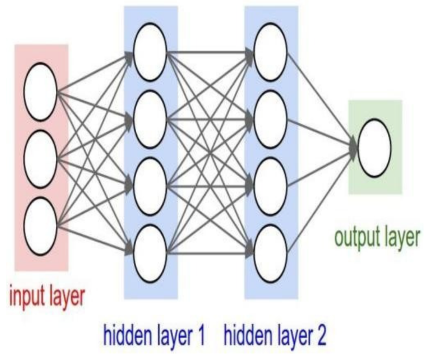


Figure: Fully-connected multi-hidden layer NN architecture.

We empirically determined the iteration numbers as 600, 750, and 1000 without constraining a stoppage criterion. Then, we added the learning rate of 0.0001 to exit the iteration between two consecutive epochs.We ran both NN methods and SVM on the same set of image data however different feature vectors based on the different feature extraction methods used

.

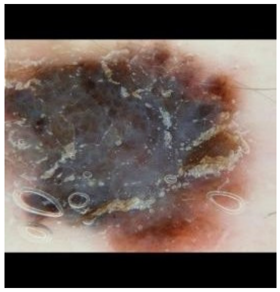
Feature Extraction-Classification	Precision	Recall	Sensitivity	F1-Score
LSP-Multilayer Perceptron NN	0.82	0.81	0.75	0.8
DS-Multilayer Perceptron NN	0.77	0.76	0.56	0.74
LSP-SVM	0.69	0.64	0.66	0.66
DS-SVM	0.62	0.61	0.61	0.61
LSP-Fully-connected multilayer NN	0.86	0.87	0.78	0.87
DS-Fully-connected multi-hidden layer NN	0.76	0.75	0.61	0.75

	NN	Parameters	SVM
Learning rate	0.001	Kernel function	Polynomial
Number of iterations	1000	Polynomial order	3
Number of runs	20	Kernel scale	Auto
Number of hidden layers	1	Box constraint	Inf
Number of hidden layer node	4	Standardize	True
Number of hidden layers (If multilayer NN is used)	4	Outlier fraction	0.05

As lower homogeneity indicates sharp cutoffs, suggesting melanoma, we carried out our experiments on two dermoscopy image datasets, which consisted of 800 benign and 200 malignant melanoma cases.By using texture homogeneity at the periphery of a lesion border determined by LSP, as a classification results, we obtained 87% f1-score and 78% specificity; that we obtained better results than in the previous study. We also compared the performances of two different NN classifiers and support vector machine classifier.

We start segmentation process by first finding the super pixels. Super pixels are one of the most popular images over-segmentation algorithms. Among many super pixel algorithms, the choice of super pixel algorithm in this thesis is Simple

[5] discussed that Liver tumor division in restorative pictures has been generally considered as of late, of which the Level set models show an uncommon potential with the advantage of overall optima and functional effectiveness.

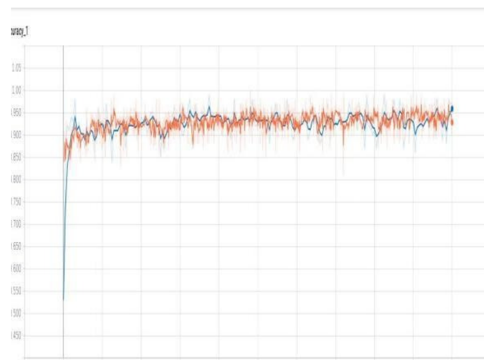


After the resizing step, we randomly split images into training and testing subsets.2,086 malignant and 2,086 benign images were in training set, and 200 malignant and 200 benign images were on testing sets. Notice that now the data is balanced.

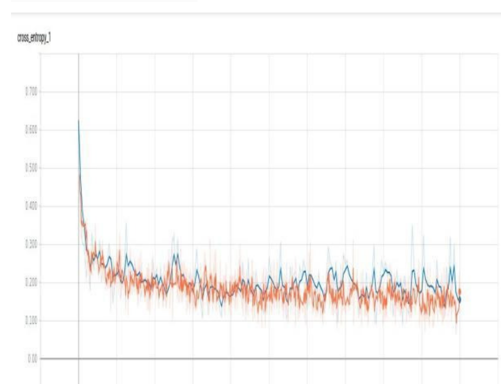
CLASSIFICATION RESULT:

Class Number	Precision	Recall	F1-Score	Support
(Benign)-0	0.97	0.92	0.94	200
(Malignant)-1	0.92	0.97	0.95	200
Average / Total	0.95	0.94	0.94	400

The classification results of experiment four were the best overall in all categories.Similar to the first two experiments, malignant class' f1-score was again higher than the benign class. Training and validation iteration results are illustrated in. This plot indicates that results are reproducible, and the algorithm is robust and reliable with high confidence for accurately classifying lesions as benign or Malignant. [8] discussed about diabetic retinopathy from retinal pictures utilizing cooperation and information on state of the art sign dealing with and picture preparing. The Pre-Processing stage remedies the lopsided lighting in fundus pictures and furthermore kills the fight in the picture. Although the Disease Classifier step was used to identify arising wounds and other data, the Division stage divides the image into two distinct classes.



These results also indicate that there is no over fitting or under fitting on the transfer learning model.Also, we examined the cross-entropy loss (log loss) which measures the performance of a classification model whose output is a probability value between 0 and 1.



With this motivation, we studied skin cancer malignancy detection to classify skin lesions and identify malignant cases.Finally, we were able to classify skin lesions with 94% average f1-score.. Also, the malignant class skin classification f1- score (95%) was higher than benign class f1-score.

CONCLUSION:

Skin cancer is increasing and affects many people every day. This cancer can be treated successfully if it is detected in early stages. Early diagnosis and treatment will lead to an increased survival chance and reduced mortality rates.. However, current clinical techniques used for the diagnosis of malignant melanoma are prone to human error due to the subjectivity and novice physicians.

This thesis proposed creative and effective methods to eliminate the subjectivity in visual interpretation of dermoscopy images and decrease the number of false- negative/false-positive diagnoses by introducing a new method for measuring abrupt cutoff and increasing the performance of feature extraction algorithms.

Abruptness of pigments on the skin is one of the most important dermoscopic features for detection of malignancy. In the current clinical setting, abruptness is determined by an examination performed by a dermatologist. This process is subjective, non-quantitative, and error-prone. We presented an improved computational model to quantitatively measure abruptness of a skin lesion by quantitatively analyzing the texture features of a region within the lesion boundary.These vectors were then classified using neural networks (NN) and SVM classifiers.

Diagnosis of malignant melanoma is the real reason of fatality due to skin cancer. Even though there are imaging and diagnosis techniques used commonly for melanoma like dermoscopy, automatic recognition is still challenging due to the difficulty of segmenting accurate lesion areas, similarity between melanoma and non-melanoma lesions and the variation of skin conditions.

Besides these problems, medical images are not easy to find while protecting the anonymity of the patients.The sum up,the objectives of this thesis were to eliminate the subjectivity on visual interpretations of dermoscopy images for abrupt cutoff and to reduce the number of false-negative/false-positive diagnosis of malignancy classifications.

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