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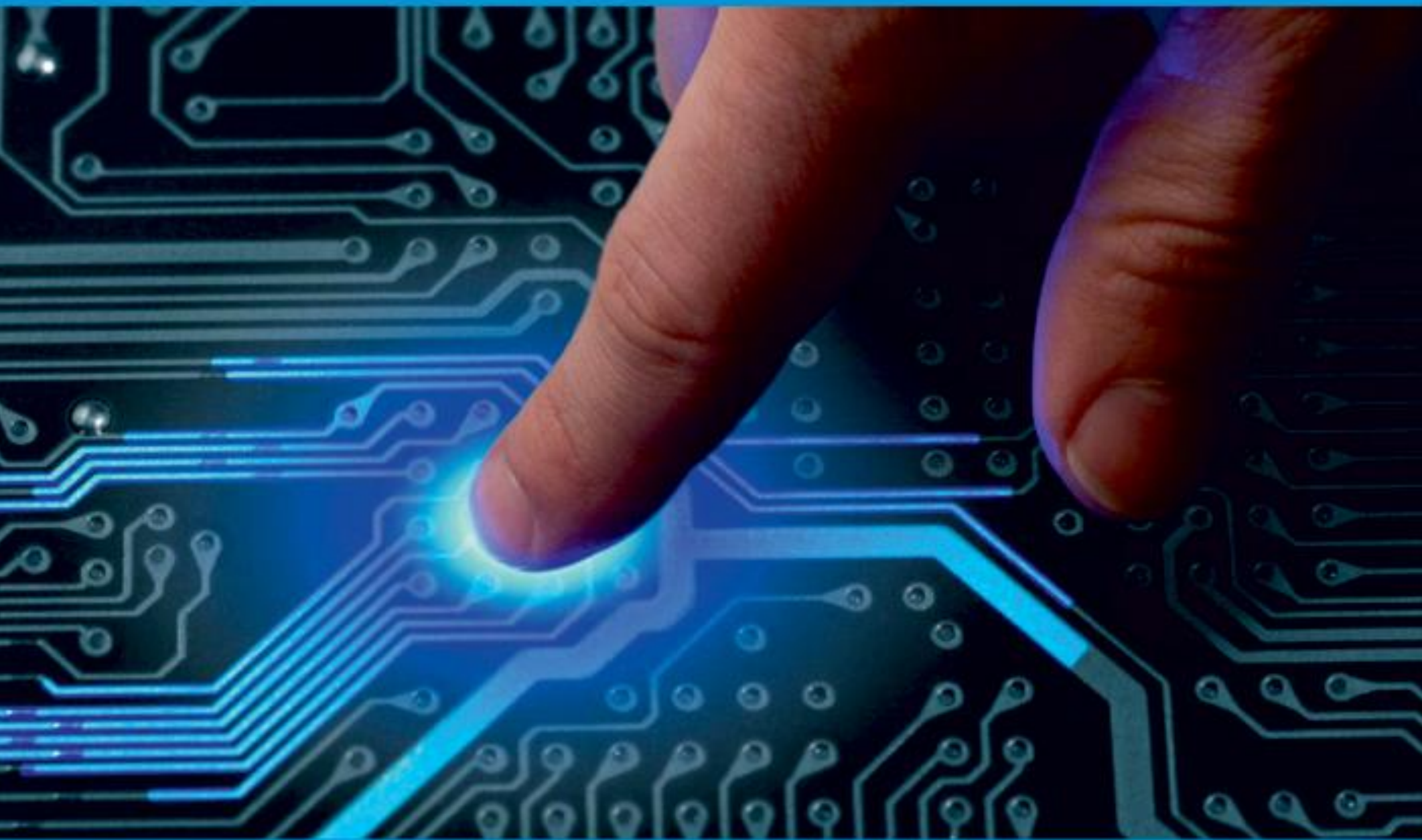

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Melanoma Classification Using Convolutional Neural Networks in Clinical Images

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ABSTRACT: The increasing number of genetic and metabolic anomalies has been determined to lead to cancer generally fatal. Cancerous cells may spread to any body part where they can be life threatening. Globally skin cancer is one of the main causes of death in humans. Early diagnosis of skin cancer acting a major role in increasing the prevention of death rate. The automated skin lesion classification has been developed to overcome the problems. The Automated skin lesion classification is a challenging task due to the fine grained variability in the visibility of skin lesions. Conventional diagnosis of skin cancer is a time consuming and tedious process. The dermoscopic images are obtained from the International Skin Image Collaboration Archive 2016. The of analysis and classification of melanoma is done with the help of a DenseNet algorithm leads to an improvement in the accuracy .The raw dermoscopic image is given as an input to the DenseNet and feature values of dermoscopic image as input to the fully connected layer as an additional information and the method gives a high classification of image accuracy.

KEYWORDS: Deep learning; DenseNet; Convolutional network

I. INTRODUCTION

The Skin cancer has been the most widespread disease globally .The occurrence of either non-melanoma or melanoma skin cancers has grown in subsequent decades. As per the World Health Organization (WHO), skin cancer can be detected in every three cases of cancer, and one out of five Americans, according to Skin Cancer Foundation Statistics, will face skin cancer throughout their lifetime. Around 7 percent of new cancer cases worldwide are caused by skin cancer. More number of peoples affected every year.

The Convolutional Neural Networks have widely been used for various classifications as well as to. The classification of skin cancers, many CNN models have dramatically outpaced highly skilled health care professionals. The given system aims at testing a deep learning approach for a melanoma classification by applying state-of-the-art pre-trained deep convolution neural networks on dermoscopy melanoma cancer databases can yield a higher diagnostic accuracy compared to dermatologists. The given approach will help clinicians for making better decisions across different skin cancer categories. The system provides a potentially low-cost system GUI application based on deep learning approach to visually screen the melanoma at the early stage, to help define the best treatment

II. RELATED WORK

A. AUTOMATIC MALIGNANT AND BENIGN SKIN CANCER CLASSIFICATION USING A HYBRID DEEP LEARNING APPROACH

The skin cancer is one of the major types of cancer with increasing in recent years. The main source of skin cancer comes in various dermatologic disorders. Skin cancer classified into various types based on texture, morphological features, color and structure. The approach for skin cancer detection requires more time and money to predict the result. Presently medical science is utilizing various tools based technologies for the classification of skin cancer The machine learning based categorization approach is the robust and leading approach for automatic methods of classifying skin cancer. The various existing and proposed methods available support vector machine, neural network, Random forest and K-nearest neighbor are used for malignant and benign skin cancer identification [1].

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B.SKIN LESIONS CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORKS IN CLINICAL IMAGES

Skin lesions are circumstances that appear on a patient due to many different reasons. One of these can be an abnormal growth in skin tissue known as cancer. Skin cancer disease affects more than 14.1 million patients and had been the cause of more than 8.2 million deaths worldwide. The solution to this problem is to find earlier diagnosis and may save lives. Finally, the network was tested with 956 original images and achieves an area under the curve (AUC) metric of 0.96 for Melanoma and 0.91 for Basal Cell Carcinoma that is comparable to state-of-the-art of results [7].

C.MELANOMA DIAGNOSIS WITH SEQUENTIAL DERMOSCOPIC IMAGES

The dermatologists over and over again diagnoses or rule out early melanoma by evaluating demoscopic images of skin lesions. The existing algorithms for early melanoma diagnosis are developed using single time point images of lesions. Ignoring the morphological and temporal changes of lesions can lead to misdiagnosis in borderline cases. Melanoma Diagnosis a framework for automated early melanoma diagnosis using sequential images [4].

PROBLEM DEFINITION

The SVM is a supervised learning method for classification, regression and outliers Extensive reviews related to medical imaging using machine learning techniques using SVM have been published. SVM-based, automated diagnostic models skin disease tends to use hand-crafted features due to their inability to extract adaptive features. The functional connectivity (FC) patterns representing disease region correlations are a popular feature of existing SVM-based diagnosis models. The SVM has been show disapproval for its poor performance on raw data and requires the expert use of design techniques to extract informative features. The various existing and proposed methods available support vector machine, neural network, Random forest and K-nearest neighbor are used for malignant and benign skin cancer identification. The accuracy and versatile of the method will be poor when compared to some deep learning approaches.

METHODS IN CONVOLUTIONAL NEURAL NETWORK

The CNN on skin images automatically classify cancerous and normal skin areas using pooling and convolutional layer for feature extraction and pattern identification. CNN evaluates the trained models on separate test images for accuracy. Basically any neural network used for image processing consists of following layers. Input layer, Convolution layer and dense layer and pooling layer. The convolutional layer is a core building block of CNN. Convolutional layer requires input data, feature map and filter. Extracts the feature from an image or video when the pooling layer convolutions the output of convolution layer. Dense layer is the simple layer of neuron each neuron receives input from all the neurons of previous layer known as dense. The dense layer classifies the image based on output from the convolutional layer. Pooling layer divide the input data into small regions called pooling windows or receptive fields then performs an aggregation operation taking maximum or average value within each window. The aggregation process reduces the size of feature maps.

DEEP LEARNING METHOD

Unlike traditional architectures, DenseNet's connections increase exponentially, improving information flow. The deep learning model allows a system to use raw data as input thereby allowing them to automatically discover highly discriminative features in the given training data set. This end-to-end learning design idea is the fundamental basis of deep learning.

Dense Block: A DenseNet consists of dense blocks and each dense block consists of convolution layers. The dense block a transition layer is added to proceed to next dense block every layer in a dense block is directly connected to all its subsequent layers. as a result, each layer receives the feature-maps of all preceding layer.

Convolutional layers : Each convolution layer is consist of three successive operations: batch normalization (BN) , followed by a rectified linear unit (ReLU) and a 3 × 3 convolution (Conv)the dropout can be added depends on the network architecture..The essential part of convolutional networks is down-sampling layers that change the size of feature-maps. The down-sampling in DenseNet architecture divides the given network into multiple densely connected dense blocks.

Transition Block: Dense Nets can scale naturally to hundreds of layers, even as exhibiting no optimization difficulties. The compact internal representations and reduced feature redundancy, Dense Nets may be good feature extractors for various computer vision tasks that build on convolutional features. The deep learning model allows a system to use raw

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data as input thereby allowing them to automatically discover highly discriminative features in the given training data set. This end-to-end learning design idea is the fundamental basis of deep learning. The main advantage of end-to-end learning is that all steps in the processing pipeline are concurrently optimized, potentially leading to optimal performance. The system provides an end-to-end hierarchy for the domain of skin disease analysis using Dense Net. The densely connected convolutional network is feed forward convolutional neural network architecture dense net links each layer to every other layer.

III. PROPOSED MODEL

A. Dataset collection*:*

The Proper datasets are required at all stages of classification research, starting from training phase to evaluating the performance of recognition algorithms. All kind of images are collected and downloaded from the internet and the dermoscopic images are obtained from the International Skin Image Collaboration Archive .The data set should be in .CSV format.

B. Image Proprocessing and Labeling

The images are downloaded from the internet are available in various formats along with different resolutions and quality. Get the better feature extraction, final images planned to be used as dataset for deep neural network classifier be preprocessed in order to gain consistency. The open source computer vision is a powerful and widely used library for image processing and computer vision tasks. OpenCV provides wide range of functions and tools that facilitate the development of applications dealing with images and videos.

C. Augmenaion Process

The augmentation is to increase the dataset and introduce slight distortion to the images augmentation helps to reducing over fitting during the training stage.

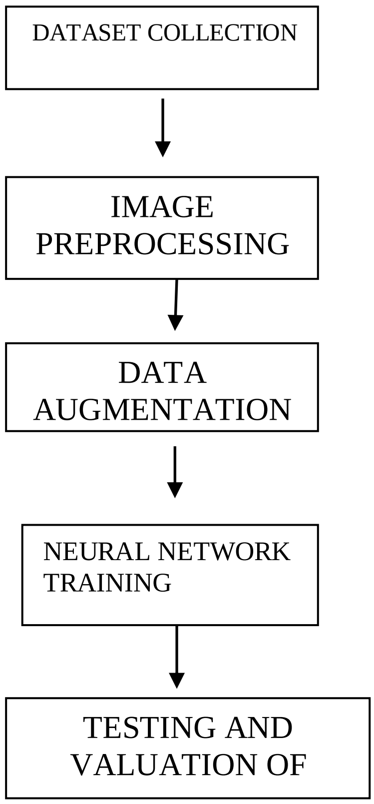

Fig 1.Flow diagram

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The data augmentation is a technique that can be used to a expand the size of a training the dataset by creating modified versions of images in the dataset. Augmentation is an integral process in deep learning method need large amounts of data and in some cases not feasible to collect thousands or millions of images, the data augmentation comes to the rescue. The Augmentation process helps to increase the size of dataset and variability in the data set.

D. Neural Network Training

The main goal of training the network is for neural network to learn the features that distinguish one class from the others. The system using more augmented images, the chance for the network to learn the appropriate features has been increased. The easiest way to build a neural network with tensor flow with sequential class of keras to develop various tasks natural language processing and image recognition.

E. Testing Trained Model with Valuation Data

Finally the trained network is used to detect the disease by processing the input images in valuation dataset and results are processed. The system provides versatile detail and high accuracy as the result. No assumptions about data – no need to make additional assumptions, tune several parameters, or build a model. This makes it crucial in nonlinear data case.

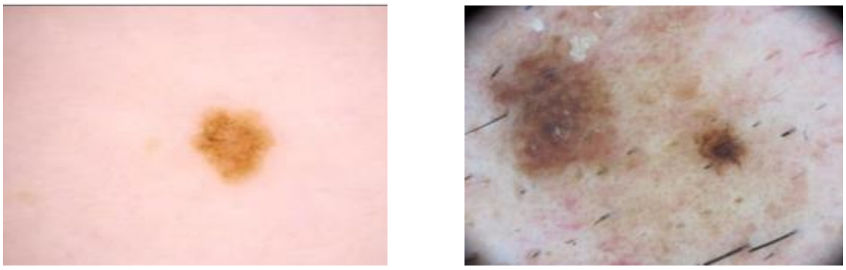

Fig 2. Benign and Malignant

IV. RESULT AND DISCUSSION

Skin cancer continues to impact communities worldwide as a deadly disease. Early detection is important to increase the patients' survival chance as the disease is fatal. In recent years, research on deep learning models in detecting skin cancer has grown substantially, given that the models offer the concept of error-less decision-making for medical applications.

Precision	recall	f1-score		support				
		0		0.90	1.00		0.95	1419
1	1.00	0.96		0.98		4356		
accuracy	0.97		5775					
macro avg	0.95	0.98		0.96		5775		
weighted avg	0.98	0.97		0.97		5775		

Fig 3. Accuracy Score

Most recently, research effort has slowly progressed towards deep convolutional neural network architectures. From what has been reviewed above, it is clear that considering CNN, data generation, and augmentation aim to mitigate insufficiency of labeled data prone to over fitting and generally improving the performance of skin lesion classification in CAD systems.

V. CONCLUSION

The recent years research on deep learning models in finding the skin cancer has grown significantly the model offers better decision and error less decision making in research applications. The research splits 70% of the dataset as a training set, 15% as the validation set, and 15% as a testing set to evaluate the performance. The proposed system developed an improved algorithm for segmentation and classification for skin lesions using CNN. The performance of the system is evaluated based on accuracy

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