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Study of Melanoma Detection and Classification Techniques

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***Abstract*: Melanoma is a type of skin cancer that starts and evolves from the pigment-producing cells known as melanocytes. There has been quite some research done in the area of melanoma classification through image detection and classification using machine learning- specifically deep learning and neural networks. Researchers have used CNN-Convolutional Neural Networks, DNN- Deep Neural Networks, some have even used RNN- Recurrent Neural Network and transfer Learning. The Research work has not been up-to the mark as of yet, we know this because there has been no news of models being put to clinical testing. Another setback to the process of creating a perfect algorithm and mode is the lack of data regarding melanoma, the largest dataset publicly available is the one provided by ISCI for its 2020 competitions it has 25333 as training data and about 8240 as testing image datasets , but the issue with these is that the do not contain just the images and data for melanoma, the are a dataset for 7 different skin lesions to be detected and classified. In this review/survey paper we will be reviewing the research work done in the past couple of years on the topic of melanoma detection and classification using Deep learning.**

Keyword- Melanoma detection, Deep learning, CNN-Convolutional Neural Networks, DNN-Deep Neural Networks, RNN- Recurrent Neural Network.

I. INTRODUCTION

"Melanoma" is one of the most dangerous and serious types of cancer (Skin), the develop in the cells called melanocytes that produce the pigment melanin. This is the pigment that gives your skin its color. This cancerous disease is also known to form in eyes and even sometimes inside one's body such=h as our nose or throat. The exact reason for this irregularity is not clear as of yet , but it is speculated and in some cases proven to be due to exposure to Ultraviolet radiations from the sun or other man made sources increases the risk of developing melanoma. The number of people effected by this seem to be increasing day by day at an increasing rate. It is seen to be increasingly effect the population under the age of 40 years especially women. Knowledge and detecting it in its early stages can help reduce the rate of fatality globaly and the number of cases of newly effected personal. In 20% cases, even surgery fails to cure it. In total skin cancer related deaths, 75% happen due to melanoma.[1]

This disease is the only one responsible for more than 50,000 cancer related fatalities around the world In the year 2015, an estimate figure of 73000 new cases was seen in the USA and approximate death rate of 2.7. It is a kind of skin lesion that can only be identified by expert dermatologists due to its close similarity to benign lesions. Diagnosis of melanoma has mostly self-processed. When the person finally registers that there is something wrong, which is due to lack of awareness and the lack of medical experts around the world. Even then the accuracy rate of melanoma detection by the experts is not that great. [2]

To reduce the pressure and to help the medical experts during the time of digital age where AI and machine learning are making leaps in the medical field, the researchers thought the need to provide the experts with a melanoma detection and classification algorithm or model. In the current research , use of deep learning for detection of malignant melanoma is carried out with a proposed architectures with benchmark datasets [1].To help with early detection of the disease, the researchers have really hit their stride in the past few years when the publicly provided slightly large datasets were provides like the HAM 10000 and the ISCI2020 set, but the issue with those is that the are not just datasets for melanoma. The HAM 10000 contains the data of seven different skin lesions, more so it is an uneven set of data which does not help with the training of neural network. In this review paper we will see how the researcher have processes their data and how have the managed to teach and build a neural network for melanoma detection, and the types of models and processes used by them to train the model and then test it on test data and validate its efficiency.

II. LITRATURE REVIEW.

We have premediated and studied some of the work previously done from the year 2015-2019. Our study and findings from the research papers have been put in a tabular form for easy access below. The table below encases the name of the authors, the classification techniques, datasets and other works done. The third column has the outcome, Accuracies of the research work done by the authors. Some of the points found in our study of the related works of the past few years is that: There is not enough data publicly available or easily accessible for research related work which causes issues. Before the ISIC provided us with the HAM10000 data set for its 2018 challenge, most of the datasets contained at maximum 1000 images, and on an avg most datasets contain 200-500 images. Most of the research work done is on various variations of the CNN architecture by changing the number of neurons or the number of hidden layers or by adding external feature extractors to help the model created with its classification.

To provide variations for the model the researchers have tried to mix and match datasets to help the model better identify melanoma for e.g. author Soumen Mukherjee Et al[1]. They have augmented image data to increase the size of the dataset. Some authors have still worked with small datasets for e.g. Zabir Al Nazi Et al[3], Savy Gulathi Et al[4],Mohammed Attia Et al[7].

TABLE I. RELATED WORKS

S.NO	AUTHOR	CLASSIFICATIN TECHNIQUE	OUTCOME
	Soumen Mukherjee Et al[1]	Datasets used by the author were Dermofit{1300} , MEDNODE{170}. They augmented images to increase dataset .CNN architecture used by them using MATLAB.	Accuracy of datasets achieved were 90.58 and 90.14%. separately and 83.07 when datasets combined.
	Zabir Al Nazi and Tasnim Azad Abir[3]	Datasets used were ISIC2018 and PH2. The author used Transfer learning.(DCNN used for feature extraction with SVM as its classifier) Images were augmented and dataset size increased.	Max accuracy of 92.00% achieved on PH2 dataset out of the many different feature extractors used DenseNet201 was the best.
	Savy Gulati(&) and Rosepreet Kaur Bhogal[4]	The authors used CAD(Computer Aided Diagnosis system) system is developed and Pretrained models used were CNN(AlexNet) and VGG16 for transfer learning and as feature extractor respectively. Dataset PH2 {200} was used in this research	The Accuracy achieved was 97%
	Felipe Moure C´ıcero Et al.[5]	This paper Focusses on classification on non malignant melanomas. Authors used the model ResNet (a CNN model by Microsoft South Korea). The Dataset was created by integrating multiple datasets{27963},and the final set Contains 24 different classes of images.	The Accuracy achieved was 60% in the 2400 test examples
	Seeja R D1, Suresh A2[6]	Authors used CNN based U-NET algorithm for Feature extraction. They used: -"Local Binary Pattern (LBP)" -"Edge Histogram (EH)" -"Histogram of Oriented Gradients (HOG)" -"Gabor method." The resultant features from the above models were fed into the: "Support Vector Machine (SVM)" "Random Forest (RF)" "K-Nearest Neighbour (KNN)" "Naïve Bayes (NB)" classifiers for classification. The Dataset used was from ISBI 2016(ISIC data)	The Accuracy achieved was 85.19%
	Mohamed Attia Et al[7]	Authors used CNN and RNN and the Dataset used for training used 900 images and tested on 375 Images. From ISBI 2016	The Accuracy achieved was 0.98
	Enes ayan Et al	The authors used CNN. And Dataset ISIC{1000}, they augmented data added to dataset{5000}.	The Accuracy achieved was Non augmented 78% ,Augmented 81%.
	Esra Mahsereci Karabulut[8] Et al	The authors used CNN and SVM and used Dataset:DermIS and DermQuest{206} LBP(local binary patterns)BDIP(block difference of inverse probabilities) for feature extraction	The Accuracy achieved was 70%
	Titus J. Brinker Et al[9]	The authors used CNN for comparison against Dermatologists{157 from different German Uni Hospitals}Dataset used were ISIC archives2018{2169 melanoma, 18566 atypical nevi images}. Test set of 100 images for both the model created and the experts..	The sensitivity and specificity achieved by the dermatologists were 67.2 and 62.2 respectively, whereas the CNN model created achieved sensitivity of 82.3% and a higher specificity of 77.9% .
	Khushboo Munir Et al[10]	The authors reviewed the papers where researchers applied deep learning models to classify different types of cancer.	Review paper.
	Noel Codella Et al.[11]	The authors used "deep learning architecture", "sparse coding", and "support vector machine (SVM)" and used the Dataset ISIC, which contained 2624 clinical cases Two-fold cross-validation: I) melanoma against all non-melanoma lesions, and II) melanoma against atypical lesions only	They achieved accuracy of 93.1% First task (sensitivity -94.9%, specificity -92.8%)., second task accuracy -73.9% (sensitivity -73.8%, specificity -74.3%) . In comparison, prior pre made models yield 91.2% accuracy.
	N. C. F. Codella Et al[11]	They used CNN(Theano, Lasagne,Nolearn python packages) Deep Residual Network (DRN) and Dataset ISBI2016	The Accuracy achieved was 0.75
	Eduardo Valle Et al[12]	Review of different models.	NA
	Andre Esteva1 Et al[13]	The authors used CNN and as Dataset they used a set of -129,450 images consisting of "2,032 different diseases" the effectiveness of the authors model was tested against "21 board-certified" dermatologists.	Three way classification accuracy 70%,Nine way classification accuracy 49% was achieved by them.
	Fujisawa1, Y. Et al[14]	The authors used DCNN architecture, which they trained on 4867 images taken from 1842 patients to classify them into 14 diagnosis of different skin lesions, the result of which is then compared against that of dermatologists.	The Accuracy achieved was 76.5%. The model achieved 96.3% sensitivity and 89.5% specificity. The accuracy of classification by dermatologists was 85.3% and 74.4%, the model achieved greater accuracy, as high as 92.4% ± 2.1%.
	Seung Seog Han Et al[15]	The researchers used "CNN(Microsoft ResNet-152" model by "Microsoft Research Asia" classifying the clinical images of 12 skin diseases. The Dataset they used, "Asan	They outcome of their proposed model had the accuracy of 91%

		dataset", "MED-NODE" , and "atlas site images"("19,398 images in total").	
	Achim Hekler Et al[16]	The reserchers used CNN and used a Dataset which contained 695 lesions that were classified by an expert histopathologist, 595 of the resulting images were used to train the model. The rest used to test it.	The Mean sensitivity=76% specificity=60% accuracy=68% was achieved in 11 test epochs. The 11 pathologists achieved a mean sensitivity=51.8 specificity=66.5 and accuracy =59.2.
	Julie Ann Acebuque Salido Et al[17]	The authors used CNN(AlexNet), Transfer learning. And for data they used PH2	The model created was able to achieve accuracy 93% for classifying melanoma and non-melanoma.
	M.H. Jafari Et al[18]	They used DCNN for making the model and Dataset: Dermquest, The used dataset has 126 digital images.	The Accuracy achieved was 98%
	M. Hossein Jafari ET al[19]	The authors used CNN and a dataset of clinical images.	The accuracy= 98.7% and, sensitivity= 95.2% in classification of lesion regions was achieved.
	Arkadiusz Kwasigroch Et al[20]	The authors used Deep Convolutional Neural Networks (CNN), The authors propose the CNN architecture and used Dataset ISIC(10000)	The efficiency of the proposed architecture was found to be 84%,authors used pre-trained neural network which caused momentous increase in accuracy, from 70.5% (CNN1) to 84% (CNN2).
	Yuexiang Li ID and Linlin Shen[21]	They used a "Fully convolutional residual networks" (FCRN).A CNN architecture is proposed for the dermoscopic feature extraction. And used Dataset: ISIC 2017	The results of the show the promising accuracies of our frameworks, i.e., task 1-0.753 , task 2- 0.848 and task 3-0.912
	Yu, Xudong Jiang Et al	They used a DRNN –"deep residual neural network" which was pre-trained on the ImageNet dataset. Then these local deep descriptors are aggregated by fisher vector (FV) encoding to build a holistic image representation, which are then classified using SVM. And Dataset was ISBI 2016 Skin lesion challenge	They achieved Avg Accuracy 85%
	Amirreza Mahbod Et al.[22]	The authors used CNNs "AlexNet", "VGG16" and "ResNet-18", as deep feature generators and Dataset ISIC 2017	They Achieved an accuracy of 83.83% for melanoma classification and 97.55% for seborrheic keratosis classification.
30	Tom´aˇs Majtner, Sule Yildirim-[23]	In this research paper the authors proposed an automatic "melanoma recognition system", which they based on deep learning method combined with "RSurf" features and "local binary patterns" LBP.they used CNN along with SVM. They used data from ISIC dataset.	Achieved classification accuracy i 0.826 sensitivity 0.533 and specificity 0.898.
\31	Tom´aˇs Majtner Et al[24]	The authors used CNN (AlexNet) with LDA Linear discriminant analysis. And Dataset: ISIC archive	Achieved Accuracy Average 82%
	Ammara Masood [25]	SVM used by authors and Dataset was collection of dermoscopic images which was obtained from different sources.	Accuracy achieved was 89%
	Afonso Menegolayz [26]	They used CNN based model and Dataset: ISBI Challenge 2016	The results favour deeper models, pretrained it on ImageNet, fine-tuning it, achieved AUC of 80.7% and 84.5% .
	E. Nasr-Esfahani, S. [27]	They used CNN and Dataset: clinical image capture "Department of Dermatology of the University Medical Center Groningen (UMCG)"	Accuracy 81% was achieved
	Abhishek Bhattacharya [28]	The authors do a pilot study to show proof of concept of DL skin pathology from a dataset of publicly available images, Review paper	NA
	Michael A. Marchetti, Et al [29]	The authors used Cross-sectional study and used 100 random images from the "international computer vision melanoma challenge" dataset (379),The authors used five methods to combine individual automated predictions into a "fusion" of algorithms. To validate they used eight dermatologists	The dermatologists achieved sensitivity and specificity of 82% and 59%,but it was still less than the proposed fusion algorithm (86% and 71%) by the authors.
	H.A. Haenssle Et al[30]	The authors have used CNN architecture for the classification model, the used the predefined model Google-inception V4. They pitted this model against an international group of 58 dermatologists who were in their level-I or -II of the reader study and used the Dataset having test-set-300 which were retrieved from the validated image library of the "Department of Dermatology, University of Heidelberg, Germany".in addition to that the authors further compared their architectures work to the top five algorithms presented in the ISBI2016 challenge. The dataset used was from the ISBI website.	The level I expert achieved a mean sensitivity of 86.6% and a specificity of 71.3%. The level II experts got a sensitivity of 88.9 and specificity of 75.7. The proposed CNN architecture achieved a specificity of 82.5 got results close to the top 3 algo of the ISBI 2016.
	J. Premaladha & K. S. Ravichandran[31]	They used Google's Inception v4 CNN and a Dataset of 992 images "(http://www.bccancer.bc.ca/HPI/SkinCancerAtlas/Melanoma/default.htm, http://www.cancer.org/cancer/skincancermelanoma/detailedguide/melanoma-skin-cancer-keystatistics, http://www.dermnet.org.nz/lesions/img/melanoma/	The Accuracy achieved was 93 %. "The proposed CAD system can assist the dermatologists to confirm the decision of the diagnosis and to avoid excisional biopsies".

		mel-is.html, http://www.meddean.luc.edu/lumen/MedEd/ medicine/dermatology/melton/content1.htm)”	
	Adria Romero Lopez[32]	The authors used VGGNet CNN architecture and transfer learning paradigm. And Dataset: ISIC Archive	The achieved sensitivity was 78.66%, which is higher than the current state of the art on that dataset.
	Yuexiang Li Et al[21]	The authors used Fully convolutional residual networks (FCRN) “A straight-forward CNN is proposed for the dermoscopic feature extraction task”. Dataset ISIC 2017.	The results show accuracy:i.e., task 1-0.753 ,task 2- 0.848 and task3- 0.912 achieved.
	Le Thu Thao[33]	They used CNN architecture and “VGG-16”,using transfer learning and Dataset used was from (ISIC)2017, which has 2000 training samples and 600 testing samples.	The Average Accuracy achieved was 0.816.
	Julia K. Winkler Et al[34]	The authors used CNN and Dataset: 120000 dermoscopic images	The CNN model achieved a sensitivity of 95.7% the study done by the authors suggest that “skin markings” significantly interfered with the CNN architectures correct diagnosis of “nevi” which was done by increasing the melanoma probability scores and consequently the false-positive rate and a specificity of 84.1%.
	Lequan Yu Et al[35]	The authors used CNN, FCRN and Dataset: ISBI 2016	The Average Accuracy 92%. Was achieved This study’s findings suggest that skin markings significantly interfered with the CNN’s correct diagnosis of nevi by increasing the melanoma probability scores and consequently the false-positive rate.
	Chanki Yu Et al[36]	The CNN method was used and Dataset of 724 dermoscopy images comprising acral melanoma they calculated the accuracy of by comparing it with the “dermatologist's and non-expert's” evaluation of the dataset.	They achieved accuracy of the CNN model created was 83.51% and 80.23%, which was found to be higher than the evaluation (67.84%, 62.71%) of any non-experts and was close to that of the dermatologists (81.08%, 81.64%).
	Xiaoqing Zhang[37]	The authors used CNN based model and the Dataset ISIC archi	The Accuracy achieved was 91%
	Karl Thurnhofer	They used CNN. Alexnet and GoogLeNet and Dataset: DermQuest Data augmentation was used to increase the number of input images.	The Accuracy of 93% was achieved.
	Hassan El-khatib1, Dan Popescu	They used CNN GoogleNet and used Dataset where All the images were extracted from the International Skin Imaging Collaboration and PH2 databases	CNN gave 80% accuracy while the classification done by the NN with 70 layers was 75%. It was the same when the classification was done with “3 targets”. The NN created gave 20%, while the CNN gave an accuracy of 57,7%.

III. METHODOLOGY:

The most commonly used methodology for most classification problems involving Deep Learning are as follows:

1. Image-Acquisition
2. Image-Pre Processing
3. Image-Augmentation
4. Feature Extraction.
5. Image-Classification.

Image-Acquisition is process of creation of a digitally encoded depiction od the visual features and characteristics of an object.in lay mans terms it is the process of acquiring a digital image of the desired object.

Image Pre Processing is the work done on an image to improve the image data as per the requirements so as to make it easier to work on the image.

Image Augmentation is the process of manipulating the image, mainly done to cover for the lack of data available. In this process we basically rotate the image by varying degrees or change the color scheme to make the system think that it is a new image.

Feature Extraction is processed to reduce the number of features in a dataset by making new features from already present ones and then discarding the original features. These new features are able to summarize most of the information contained in the original features.

Image Classification- deep learning now excels in recognizing objects in a image as it is supposed to be implemented using 3 or more layers of ANN where each layer is responsible for extracting one or more features of the image being used for classification.

The methodology observed in most of the research work done on melanoma beginning with acquiring of datasets. Which is one of the biggest hurdles presented in this. A proper large dataset of skin lesion images was only provided publicly in the last 2 years in the ISIC challenge 2018-2019 where a huge set of 10015 and 25333(train) images was provided, but the issue with these datasets is that, the are not only the sets containing the images of melanoma, but contain 7 skin images of seven different skin lesions. This can be a bit of a hindrance while training a model for melanoma detection. As it reduces the accuracy of the model due to uneven balance of the number of images provided for each class.

For example we have a dataset containing of images from 3 classes A, B, C respectively. The distribution of data is of the ratio 6:2:2 respectively. Now, when we train the neural network, it learns that if it gives the classification as A most of the time it would achieve the most accuracy easily which is not the aim of the project. To counter this, we could use weights to inform the NN to evaluate some classes according to the weights or we could use the process of random oversampling or random under- sampling. oversampling is a process in which we use data augmentation to increase the number of images in classes with low quantity. Under-sampling is the process od reducing the image quantity of large quantity classes to match that of low ones. Some of the other datasets used are: PH2,ISIC2018, ISBI2016, DermQuest, Dermofit, MEDNODE, DermIS, ISIC 2017 .

After acquiring the data is the data preprocessing phase, where the data is reshaped to the required template, resized, Etc. Then if required the data is sent for augmentation, its s mainly done to increase the number of images.

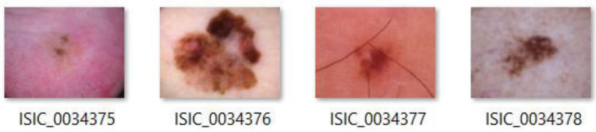

Fig. 1.

Most of the work done is seen to be using CNN(Convolutional Neural Network) for feature extraction and Image classification which it does automatically. As it was mainly developed for image classification

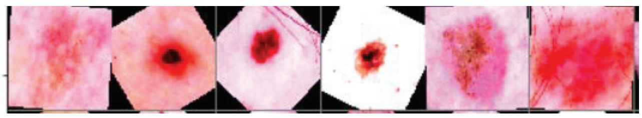

Fig. 2.

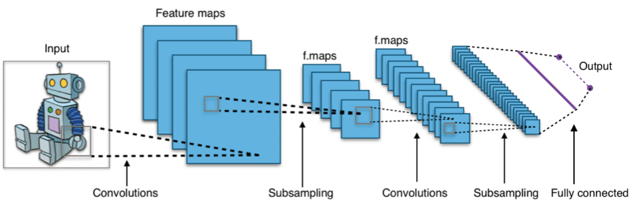

Fig. 3. .

The CNN gained fame through its work done by researchers with image data. The general CNN architecture is as follows:

“Convolution->Pooling->Convolution->Pooling->Full connected Layer->Output”.

Convolution is the process of taking the original data and creating feature maps from it . Pooling is the down sampling which is mostly done in the form of “MAX POOLING” where a region is selected and then the max value of that region is taken and then that value becomes the new value for the entire region. Fully connected layers are your typical Neural Networks, where all the nodes are completely connected to each other.

IV. CONCLUSION:

We can see from the above compiled data of related research done in past few years, that most of the work is done using Neural Networks, Deep Learning, specifically CNN Convolutional Neural Networks. It is so because with the advancement in the field of AI models have been created which can automatically extract features and learn from them. Most of the work done has been done on some variation of the CNN, e.g. using different no. of hidden layer, using external feature extractors to help with the classification etc. some have even used the pre trained models of CNN like the AlexNet etc. lack of publicly available data can be seen from the study , some of the data sets have just 100-200 images which is really low , considering we need to train a neural network. The data was augmented by processing and changing the degree of rotation to make the system feel as if it was a new image, there are even some libraries create specifically for data preprocessing and augmentation. There were a number of external models used for feature extraction by the authors e.g. -Local Binary Pattern (LBP), -Edge Histogram (EH), -Histogram of Oriented Gradients (HOG)-Gabor method. These authors used these architectures to support the classification model in in identifying the image. The classification is done by the CNN architecture mostly, Keras has provided us with inbuilt functions that make it easy to personalize and create a neural network with CNN architecture. We plan to create and work on our own personal model of CNN for classification of melanoma with our own version of twists.

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