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SKIN CANCER DETECTION WITH ASSISTANCE OF INTERACTIVE CHATBOT

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Abstract— Cancer is one of the most widespread diseases on the planet. Cancer exists in different forms and also occurs at different parts of the human body. Cancer claims close to 5 million lives every year and a considerable portion of this includes the skin cancer cases. Cancer is basically the abnormal growth in the cells of the human body which can be caused by physical, chemical or biological carcinogens in a staged and a gradual process. Skin cancer basically means an abnormality in the growth of skin cells which results in a tumorous growth of the skin cells. On a whole, skin cancer can be classified into 4 major categories - Actinic Keratoses, Basal Cell Carcinoma, Squamous cell carcinoma and Melanoma. Our project aims at creating a highly accurate and a highly optimized version of the classifier of the different types of skin cancer by using different types of Image Processing and Image Recognition techniques involving segmentation and Convolutional Neural Networks. Another aspect of the project is to classify a particular skin image into non-cancerous skin diseases**.**

Index Terms— Machine Learning, Convolution Neural Network, Deep Learning, Melanoma, Feature Extraction, Skin Cancer, Lesion Classification

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1. Introduction

In the past 10-year period, from 2008 to 2018, the annual number of melanoma cases has increased by 53%, partly due to increased UV exposure. On a whole, skin cancer can be classified into 4 major categories - Actinic Keratoses, Basal Cell Carcinoma,
Squamous cell carcinoma and Melanoma, out of which Melanoma is one of the most lethal types. Anyhow, early diagnosis can lead to a very high chance of survival. According to the WHOś statistics, the number of people affected by skin cancer will rise up to almost 13.1 millions by 2030. Skin cancer is a condition in which there is an abnormal growth of melanocytic cells in the skin. Melanocytes are the pigment-containing cells which are responsible for Melanoma type. Melanoma is found among non-Hispanic white males and females, and results in approximately 75% of deaths associated with skin cancer. According to the world cancer report, the primitive reason for melanoma is ultraviolet light exposure in those people who have low levels of skin pigment. The UV ray can be from the sun or any other sources and approximately 25% of malignant can be from moles.
Neural Network algorithm is utilized to detect the benign and malignant. This framework is based on learning the images that are captured with a dermatoscopic device to find out whether it is benign or malignant.
Convolutional Neural Network (CNN) is the most well-known for image recognition and classification algorithms. CNN is chosen because it gives high accuracy in image processing. CNN has four working standards.

- The primary layer fills in as an input layer where dermatologists give everyone of the information they obtained. The input layer at that point forms the information and sends it to the next layer which is then sent to the pooling layer.

- The pooling layer pools the information structure by performing max pool or min pool. After that, the information gets into the thick layer and then converted into the class based on situation, benign or malignant.

This paper represents an automatic skin cancer detection approach based on convolutional neural networks to classify the cancer images into either malignant or benign melanoma.

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2. LITERATURE SURVEY / RELATED WORK

1.1 In contrast to Gutman et al [1] , however, Codella et al [2] used a total of 2624 dermatoscopic images from the publicly available International Skin Imaging Collaboration (ISIC) database for the classification of melanoma versus non melanoma lesions or melanoma versus atypical nevi. In addition to the modified AlexNet outputs, the authors also used low-level handcrafted features and features from sparse coding, a deep residual network, and a convolutional U-network. Classification based on all of these features was then performed using a support vector machine. The authors reported an accuracy of 93.1%, a sensitivity of 94.9%, and a specificity of 92.8% for classifying melanoma versus nonmelanoma. In the more difficult discrimination between melanomas and atypical nevi, an accuracy of 73.9%, a sensitivity of 73.8%, and a specificity of 74.3% were reported. The authors also showed that the use of deep features results in a better performance compared to classifiers that only used low-level handcrafted features.

1.2 Kawahara et al [3] used a linear classifier to classify 10 different skin lesions. Feature extraction was also performed using an AlexNet whose last fully connected layer was replaced with a convolutional layer. This slightly modified AlexNet was tested using the public Dermofit Image Library, which contains 1300 clinical images of 10 skin lesions. An accuracy of 81.8% was achieved based on the entire dataset of 10 different types of skin lesions.

1.3 Esteva et al [4] presented a landmark publication. For the first time, a CNN model was trained with a large amount of data, specifically 129,450 images, of which 3374 were obtained from dermatoscopic devices and represented 2032 different skin lesions. Two binary classification problems were considered: keratinocyte carcinomas versus benign seborrheic keratosis and malignant melanomas versus benign nevi. The last classification differentiation was performed for both clinical and dermatoscopic images. The authors used a GoogLeNet Inception v3 model for the classification, which was pretrained with the large image database ImageNet. The CNN model was then fine-tuned to classify skin lesions using transfer learning.

1.4 Han et al [5] are particularly noteworthy for their scientific transparency since they have made their computer algorithm publicly available for external testing. The team presented a classifier for 12 different skin diseases based on clinical images. They developed a ResNet model that was fine-tuned with 19,398 training images. With the publicly available Asan dataset, the CNN model achieved ROC AUCs for the diagnosis of basal cell carcinoma, squamous cell carcinoma, intraepithelial carcinoma, and melanoma of .96, .83, .82, and .96, respectively

1.5 A special architecture of a CNN ensemble is presented by Kawahara et al [6] . The CNN was composed of multiple parts in which each part considers the same image at a different resolution. Next, an end layer combines the outputs from multiple resolutions into a single layer. The CNN identifies interactions across different image resolutions and the weighting parameters are completely optimized by end-to-end learning. The algorithm achieved an average classification accuracy of 79.5% in the public Dermofit Image Library.

In Nasr-Esfahani et al [7] , a two-layer CNN was trained from scratch for the distinction of melanoma versus benign nevi based on clinical images. Only 136 images were used to train the model and the test dataset contained only 34 images. The images were all from the public image archive of the Department of Dermatology of the University Medical Center Groningen. The method achieved a sensitivity of 81%, a specificity of 80%, and an accuracy of 81%. However, the result should be viewed critically because the test dataset was very limited.

1.6 Andre Esteva, Brett Kuprel, Roberto A. Novoa,Justin Ko, Susan M. Swetter, Helen M. Blau & Sebastian Thrun, Dermatologist-level classification of skin cancer with deep neural networks, Nature Vol 542, 2017 [9] The system uses Convolutional Neural Networks. Algorithms use taxonomy to partition the diseases into finely-grained training classes. The images which are blurry, noisy or have been taken from a distance have been removed from the testing set but have been kept in the training set. This makes the entire system extremely fault tolerant. Training algorithm used is Google's Inception system uses a deep neural network which enables the system to extract the local features of an image and brings it very close to how a human sees and visualises an image.The accuracy of the system is 93.33% which is one of the top 5 accuracies on the 1000 object classes. Tackling this problem by means of a LSTM Network(Long Short Term Memory Network) will make themodel much more accurate

1.7 Titus Josef Brinker, Classification of Skin Cancer using Convolutional Neural Networks, JMIR, 2018 [10] The project uses CNN which is already trained using some large dataset in which optimizes the performance of the neural network by tuning and optimizing the parameters and hyperparameters This approach of optimization of a currently employed CNN is one of the most accurate and best performing systems out there The disadvantage remains the lack of memory in this case. A hybrid network which will include the performance of a CNN and an LSTM can be worked upon in the future which will take the accuracy of Skin Cancer Detection models as close as possible to a perfect model.

1.8 Skin Cancer Detection using Artificial Neural Network Ekta Singhal Shamik Tiwari International Journal of Advanced Research in Computer Science Volume 6, No. 1, Jan-Feb 2015 [11] For feature extraction technique,they have used Multilevel 2-D wavelet decomposition . Back propagation neural network and radial basis neural network are used for classification purpose, which categorizes the given images into cancerous or The proposed method gives 92% accuracy with BPNN and 88% accuracy with RBFNN using a haar wavelet. RBFNN has less accuracy but it has good generalization ability. In future,this method if improvised and would detect the cancer at an early stage and provide a significant breakthrough.

1.9 Skin Cancer Detection Using Image Processing Uzma Bano Ansari Tanuja Sarode Volume: 04 Issue:04 | Apr -2017 [12] International Research Journal of Engineering and Technology (IRJET) The SVM algorithm is used as an algorithm for classification purposes. Various pre-processing techniques applied to reduce Noise and enhance the image. Also the segmentation is done using the Threshold method. Features extracted using GLCM methodology. Accuracy of the proposed system is 95%. It is a painless process than the biopsy method. There is a scope of improvement in accuracy as it is a medical field and the margin of error should be minimum.

1.10 Pracharya Bumurgun and Wisaran Patchoo Detecting Skin Cancer Using Svm and Snake model [13]. Here they apply SVM for finding proper initial curve and parameters for Snake algorithm.They find the edge by Snake algorithm and unwanted areas are removed by False Classification using SVM The output image shown can see the edge of picture .When compare to the edges found By professionals the edge are closed to the expert. It will not be good for the preprocessing the images Some more elaborate classification and and refinements are required for better segmentation result

2.2 Methodology

At present, if a patient needs to recognise whether they have skin disease or not, they have to undergo singular screening. To make this process quick, there are a few number of symptomatic checklists that have been established.

ABCDE is one of the checklists.

➔ Asymmetry(A) - One portion of the affected cell that has turned into a tumor does not coordinate the other half. Wattage for this factor is 1.3.

➔ Border(B)- The edges/the fringe of the tainted cells wind up battered, scored, obscured. Wattage for this factor is 0.1.

➔ Color(C)- Shades of tan or dark colored spots on skin and dark are available. Dashes of red, white and blue add to the repulsive appearance. They aren't uniform. Wattage for this factor is 0.5.

➔ Diameter(D)- The cell width ends up more noteworthy than 6mm and over.

➔ Evolution(E)- Previously mentioned changes or advancements show Malignant Melanoma

We followed following approach in our project,

1. Obtaining the data

The project has been built on Google Collab so we have obtained a dataset from kaggle using kaggle API. Data imported from kaggle was in ZIP format. Therefore we have used the ZipFile class from the Python Zipfile packagein order to extract the data on cloud.

2. Image Processing

We have created a function called Noisy which will add Poisson, Gauss or Salt-and-pepper noise based on the parameters passed. Every image is read using the OpenCV library. A random noise from the three is added.

3. Image Restoration

Median filter works the best from the three provided noises.Therefore,we have median filtering in Image restoration.The Median Filter is a non-linear digital filtering technique, often used to remove noise from an image or signal. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image.

4. Image Enhancement

It has been done using histogram equalisation. Histogram equalisation is a technique for adjusting image intensities to enhance contrast. Let f be a given image represented as a mr by mc matrix of integer pixel intensities ranging. from 0 to L − 1. L is the number of possible intensity values, often 256 .

5. Image Segmentation

We have used thresholding segmentation. The dataset contains images having distinct tumor regions and background skin. Therefore,thresholding segmentation by setting the mean of the entire image as the threshold will work in this case.

6. Data Processing

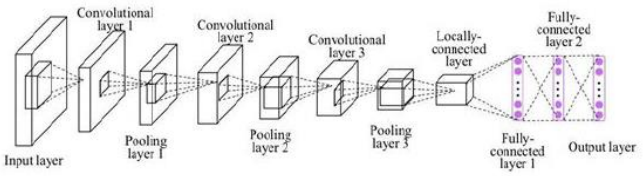
Libraries used are

i) OpenCV,
ii) Matplotlib,
iii) Sys,
iv) Pandas,
v) Os,
vi) Glob,
vii) Numpy,
viii) random.

The images extracted were in two different folders : Part 1 and Part2. In order to get the image-path, we've used the glob library and created a dictionary having image name as the key and path as the value. Then,the Pandas-library is used to read the metadata.After that,the dictionary is mapped to the Pandas dataframe and a new column of image_path is added to the df.Now the image is read by the use of OpenCv library and each individual image is resized to 100x100.Image is read in grayscale.The image and the label is stored as a set of list ([image,label]).Now the entire list is shuffled using the random shuffle function.The features and labels are then separated into 2 different lists, X and y.

The overview and details of concepts we used are as follows,

a. Architecture



Layer	No. Of Units	Kernel Size

Conv1	**32**	**3x3**
MaxPooling1	**32**	**2x2**
Conv2	**64**	**3x3**
MaxPooling2	**64**	**2x2**
Conv3	**128**	**3x3**
MaxPooling3	**128**	**2x2**

b. Optimiser Used

Adam Optimizer -

Adam Optimizer functions similar to a normal gradient descent. The difference between adamoptimizer and gradient descent is that in Adam optimizer, the learning rate is more initially but it decreases as the number of completed epochs increase.

c. Input Layer

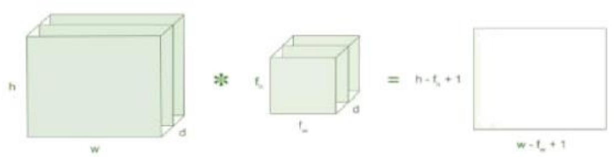
The images are of 600x450 format. However, such large images will require exponentially huge computation power in order to train the image. Therefore, we have resized the imageusing the opencv library to a 100x100 image.

d. Convolutional Neural Network (CNN) — Deep Learning

In neural networks, Convolutional neural networks is one of the main categories to do image recognition, images classifications. Objects detections, recognition faces etc., are some of the areas where CNNs are widely used. CNN image classifications take an input image, process it and classify it under certain categories (Eg., Dog, Cat, Tiger, Lion). Computers see an input image as an array of pixels and it depends on the image resolution. Based on the image resolution, it will see h x w x d (h = Height, w = Width, d = Dimension).

Example, an image of 6 x 6 x 3 array of matrix of RGB (3 refers to RGB values) and an image of 4 x 4 x 1 array of matrix of grayscale image.

- An image matrix (volume) of dimension **(h x w x d)**
- A filter **(f_h x f_w x d)**
- Outputs a volume dimension **(h - f_h + 1) x (w - f_w + 1) x 1**



e. **Tech Stack used**

Language used,

- Python
- Libraries used,
- Tensorflow - for implementing the complete neural net-work
- Opencv - for image manipulation operations
- Pandas - for reading the data frame
- Os - for getting the images from a folder locally saved on the system
- Matplotlib - for plotting and showing the image.
- CNN image classifications take an input image, process it and classify it under certain categories (Eg., Dog, Cat, Tiger, Lion). Computers see an input image as an array of pixels and it depends on the image resolution. Based on the image resolution, it will see h x w x d(h = Height, w = Width, d = Dimension). Eg., An image of 6 x 6 x 3 array of matrix of RGB (3 refers to RGB values) and an image of 4 x 4 x 1 array of matrix of grayscale image

2.3 **EXPERIMENTAL RESULTS AND DISCUSSION**

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1. Dataset Description

The dataset we will be using for this project is the HARVARD HAM10000 dataset: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T

The dataset consists of 10015 dermatoscopic images which can serve as a training set for academic machine learning purposes. Collected dermatoscopic images from different populations, acquired and stored by different modalities.Cases include a representative collection of all important diagnostic categories.

Due to upload size limitations, images are stored in two files:

● HAM10000_images_part1.zip (5000 JPEG files)

● HAM10000_images_part2.zip (5015 JPEG files)

This dataset contains images of 7 classes:

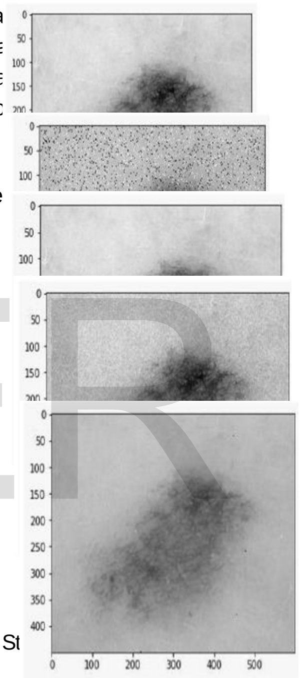
1. Benign
2. Actinic Keratosis
3. Intraepithelia
4. Boen's Disea
5. Basal cell Ca
6. Dermatofibro
7. Melanoma

2. Expe

2.1

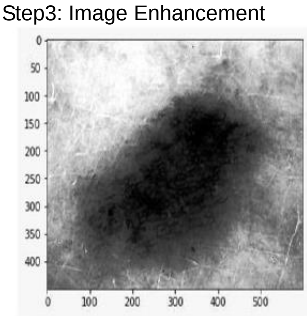
2.2

St



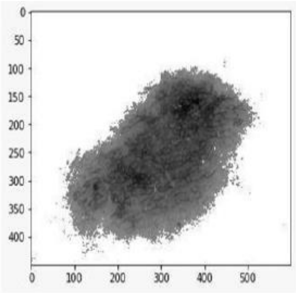
Restored Image

Step3: Image Enhancement



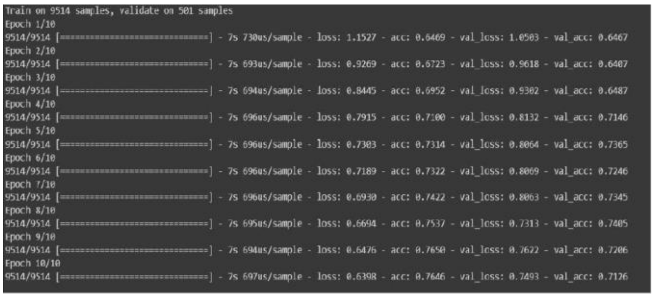
Enhanced Image

Step4: Image Segmentation



Segmented Image

2.3 Explanation and Interpretation of results



```
Train on 9514 samples, validate on 501 samples
Epoch 1/10
9514/9514 [==============================] - 7s 730us/sample - loss: 1.1527 - acc: 0.6469 - val_loss: 1.0503 - val_acc: 0.6467
Epoch 2/10
9514/9514 [==============================] - 7s 693us/sample - loss: 0.9269 - acc: 0.6723 - val_loss: 0.9618 - val_acc: 0.6407
Epoch 3/10
9514/9514 [==============================] - 7s 694us/sample - loss: 0.8445 - acc: 0.6952 - val_loss: 0.9302 - val_acc: 0.6487
Epoch 4/10
9514/9514 [==============================] - 7s 696us/sample - loss: 0.7915 - acc: 0.7100 - val_loss: 0.8132 - val_acc: 0.7146
Epoch 5/10
9514/9514 [==============================] - 7s 696us/sample - loss: 0.7303 - acc: 0.7314 - val_loss: 0.8064 - val_acc: 0.7365
Epoch 6/10
9514/9514 [==============================] - 7s 696us/sample - loss: 0.7189 - acc: 0.7322 - val_loss: 0.8069 - val_acc: 0.7246
Epoch 7/10
9514/9514 [==============================] - 7s 696us/sample - loss: 0.6930 - acc: 0.7422 - val_loss: 0.8063 - val_acc: 0.7345
Epoch 8/10
9514/9514 [==============================] - 7s 695us/sample - loss: 0.6694 - acc: 0.7537 - val_loss: 0.7313 - val_acc: 0.7405
Epoch 9/10
9514/9514 [==============================] - 7s 694us/sample - loss: 0.6476 - acc: 0.7650 - val_loss: 0.7622 - val_acc: 0.7206
Epoch 10/10
9514/9514 [==============================] - 7s 697us/sample - loss: 0.6398 - acc: 0.7646 - val_loss: 0.7493 - val_acc: 0.7126
```

- In CNN, we used normal distribution, “glorot_normal” for kernel initialisers. Another option we had in Glorot class was “glorot_uniform”. So, many studies out there used uniform but it still is a doubt which one is better among them. As compared to other classes, zero, random, orthogonal, variance scaling, glorot class is most efficient and best suited for implementation that involves digital processing functions.
- After that, we use activation function to main/increase non-linearity. For that we used “ReLU”. It stands for Rectified Linear Unit. The main advantage of using the ReLU function over other activation functions is that it does not activate all the neurons at the same time. This means that the neurons will only be deactivated if the output of the linear transformation is less than 0. For the negative input values, the result is zero, that means the neuron does not get activated. Since only a certain number of neurons are activated, the ReLU function is far more computationally efficient when compared to the sigmoid and tanh function.
- We used Adam optimizer instead of gradient descent. Benefit is that the learning rate is more initially but it decreases as the number of completed epochs increase.
- For the input layer we had to resize the image to 100X100 to make the processing easy using OpenCv library as the origin resolution was much higher, around 600X450.
- We added 7 layers in our CNN for more accuracy. As you can see the batch size is standard 128 and we stated 10 epochs.

2.4 PERFORMANCE AND EVALUATION

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1. Metrics

- To assess the model, accuracy, recall, precision, specificity and f1 score are utilized to determine the performance of the proposed model. Here, Recall is what number of threatening cases can distinguish out of complete given dangerous cases.

Recall = TruePositive / Positive

- Specificity is what number of benign cases can recognize out of complete given favorable cases.

Specificity = TrueNegative / Negative

- Precision is what number of threatening cases model could foresee effectively out the all out cases it anticipated as harmful

Precision = TruePositive / TruePositive + FalsePositive

- F1-score is a consolidation of precision and recall to admit the fundamental concept on how this system works

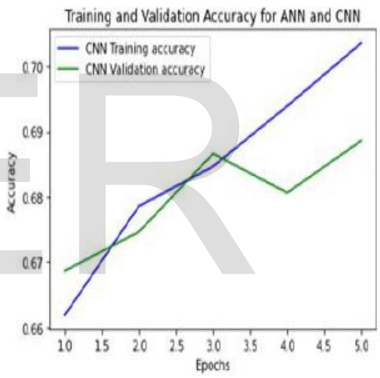
FMeasures = 2 × Precision × Recall/Precision + Recall

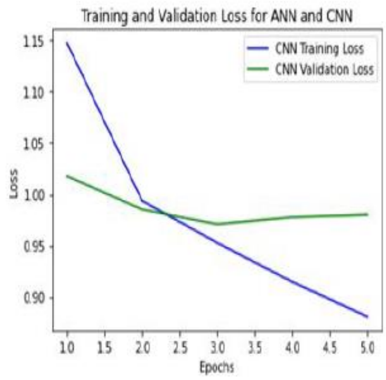
2. Comparison with existing system

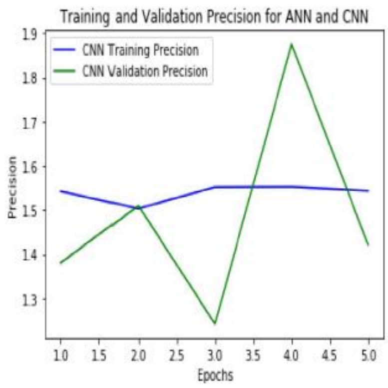
Unfortunately, it is difficult and in many times impossible to compare the performance of published classification results since many authors use nonpublic datasets for training and/or testing. Future publications should use publicly available benchmarks and fully disclose methods used for training to allow comparability.

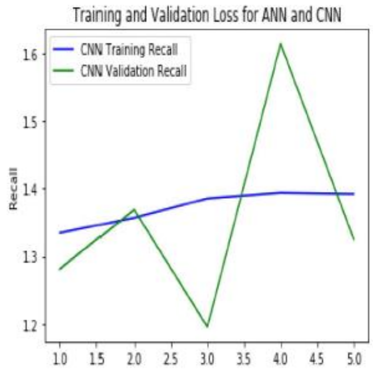
So, on our personal level, we tried different models of CNN. After comparing accuracy, we found out Sequential CNN model has the highest accuracy.

3. Interpretation of current system (tables and graph)









4. Conclusion of evaluation metrics

S.NO	**Split (Train/Test)**	**Accuracy**	**Loss**	**F1**	**Recall**
1	75/75	0.6687	1.0177	1.6183	1.4419
2	75/75	0.6747	0.9853	1.7406	1.5306
3	75/75	0.6866	0.9708	1.6796	1.4879
4	75/75	0.6806	0.9779	1.4810	1.3588
5	75/75	0.6886	0.9802	1.5462	1.3901

We obtained a plot of loss, to analyse the loss function in CNN and ANN on our model with increase in epochs. Similarly we repeated the process for F1score and recall values and put them into a table. From the table given, we can derive results that the accuracy is highest with the test/ train split being 90-10%.
We could conclude that depending upon the training/validation split and the accuracy of the project was around the 68% mark. In the paper, “Superior skin cancer classification by the combination of human and artificial intelligence” have mentioned their accuracy by the combination of human effort and machine to be 82.95%. The highest accuracy achieved by a CNN model in this data set is 81.59% and that by Human Intelligence is about 42.94%.

3 CONCLUSION

We all know that skin cancer has multiplied to such an extent that it’s very important to detect the disease at its initial stages. After carrying a survey on around fifteen research papers, we can draw the inference that there is still a lot of scope for research in the field of image processing for skin cancer detection and it can be furthermore used to reduce the number of deaths caused by melanoma and other kinds of cancer. Image-based computer aided diagnosis systems have a much significant potential for screening and early detection of malignant melanoma. We reviewed the state of the art in these systems and then examined the current practices, problems, and prospects of image acquisition, pre-processing segmentation, feature extraction and selection, and classification of dermoscopic images.

So, we have come up with the method of image segmentation to detect early signs of skin cancer due to raised concentration in certain parts of the skin. We have used the concepts of deep learning and Convolutional Neural Network to detect the same and prove its efficiency. For formulating the code we have used the Sequential CNN model.We used it for the neural network architecture because they can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. We added 7 layers in our CNN for more accuracy. As you can see the batch size is standard 128 and we stated 10 epochs.

On analysing the performance of our model we get the following plot showing us the accuracies for ANN and CNN architecture respectively. We can clearly see that our CNN model is way more accurate as the epochs increase.

The present algorithm is fast, takes very few seconds of execution time and results are found to be good with the accuracy of about 68%. It can be concluded from the network results that the suggested system can be capably used by patients and physicians to diagnose skin cancer more exactly. This tool is useful for the rural areas where the experts in the diagnosis field may not be applicable. Since the tool is made more feasible and robust for images acquired in any conditions, it can deliver the purpose of automatic diagnostics of Melanoma Skin Cancer.

In future, we could develop a computer algorithm for skin cancer diagnosis using Support Vector Machine, which is also an emerging technology nowadays.

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