Detecting Skin Cancer Using Deep Learning

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***Abstract*— One of the most prevalent types of cancer around the United States and globe is skin cancer. Every 1 person in 6 will have skin cancer after the age of 65 and more than 3 people pass away because of it every 60 minutes in United states. One of the most serious types of cancer among them is melanoma. If diagnosed it early the life expectancy rate of 5 year is 99% only. These statistics are very surprising. The situation is even worse in more of the poor countries. To detect the skin cancer and its type in very early stage is most crucial task to prevent it from the spreading. The computer vision can be integrated to solve the issue in some way. Therefore, in this research paper we have constructed deep learning algorithm to detect the type of cancer. The standard and widely used deep learning algorithm, Convolutional Neural Network (CNN) is preferred to detect and categorize the cancer into different classes. The motive of this research is to integrate deep learning with global medical problem to recognize the type of skin cancer, so it can be recovered with medical treatment at early stages. The accuracy achieved in this study with CNN architecture is 97.27%**

Keywords—CNN, Neural Network, Lesions, Skin

I. INTRODUCTION

Skin cancer is a disease which occurs in more than a million people every year. There are three types of it-basal cell carcinoma(bcc), benign keratosis-like lesions(bkl), melanoma(mel), Actinic keratoese and intraepithelial carcinoma(akiec), dermatofibroma(df), vascular lesions(vasc) and melanocytic nevi(nv).

Melanoma is one of the worst form of skin cancer which grows in the cells (melanocytes) that create melanin which is a pigment that gives your skin its color. Basal cell tumors develop in the skin from aberrant basal cells. It is rarely lethal, but it can be aggressive locally. A seborrheic keratosis (pronounced seb-o-REE-ik ker-uh-TOE-sis) is a benign (noncancerous) skin development. As people age, they become increasingly prevalent. Seborrheic keratoses are often brown, black, or light tan in color. The lesions seem waxy and somewhat elevated. Actinic keratosis (AK) is a skin condition that develops rough, scaly patches of skin. Solar keratosis is another term for AK. AK is a form of precancer, which means that if it is not treated, it can progress to cancer. Without treatment, AK can progress to a kind of skin cancer known as squamous cell carcinoma. Noncancerous skin growth is cellular dermatofibroma. It could resemble a small, firm protrusion, comparable to a mole. Vascular lesions, often known as birthmarks, are very common skin and underlying tissue abnormalities. Melanocytic nevi are more common in patients with light or fair complexion and less common in patients with dark skin.

Skin cancer is caused when a person is overexposed to sunlight. When a person suffers from sunburn or blistering, the UV rays from the sun damage the DNA in the skin which leads to formation of abnormal cells. Later, these cells are rapidly divided, forming mass cells of cancer.

Nearly in 85% of them, the skin damage is caused before the individual turns 18. Thus, an early discovery and screening for skin cancer, like with all cancers, is the most promising sign of a full recovery. Early identification of skin cancer results in a 94% ten-year survival rate. However, as cancer advances and reaches the next stages, the survival rate lowers dramatically. When Melanoma is identified in its latter stages, ten-year survival rates are as low as 15%.

As this is an alarming disease, an early diagnosis of this condition is necessary. Because of its non-invasiveness, image processing has been proposed in many research papers for the identification of melanoma skin cancer, and it has increasingly become an efficient diagnostic tool for medical images accurate interpretation, and thus early and appropriate treatment can be administered to the patient.

In this project, a deep learning approach is used to classify skin lesions in various skin cancers. Convolutional Neural Network is applied on a set of image data which multi-classifies the image into 7 types of lesions basal cell carcinoma(bcc), benign keratosis-like lesions(bkl), melanoma(mel), Actinic keratoese and intraepithelial carcinoma(akiec), dermatofibroma(df), vascular lesions(vasc) and melanocytic nevi(nv).. The data for this experiment was taken from Harvard Dataverse.

II. RELATED WORK

A nonlinear neural network classifier is used to classify skin lesions based on in vitro Raman spectroscopy. The approach for categorization is probabilistic and highly automated. BCC, the most frequent type of skin cancer, with a categorization rate of 95.8 percent 2.7 percent.[1]. In this paper, the researchers have proposed a method for detecting and classifying skin lesions as benign or malignant using images from standard cameras.[2] On a dataset of 463 photos which was classified into six unique classes, the trained Neural Networks achieved an overall accuracy of 76.9%

The researchers have proposed an early skin cancer detection system. Support Vector Machine (SVM) and image processing methods are used in the diagnosing methodology. Here,[3] the dermoscopy image of the skin cancer was captured which was pre-processed for enhancement and noise removal. Some features of the image were extracted using GLCM methodology which were given as an input to the SVM classifier. An accuracy of 95% was achieved.The authors [4] explored a computer-aided diagnosis technique for melanoma skin cancer in this research. Asymmetry,

Border, Color, Diameter (ABCD), and other Melanoma characteristics are checked using lesion image analysis techniques. These techniques can be efficiently used by patients as well as physicians to diagnose skin cancer.The paper [5] is a first systematic review of state-of-art research on classification of skin lesions with CNNs. As some approaches use nonpublic datasets, it is very difficult to compare different methods. CNN method has the best performance as a state-of-art skin lesions classifier.

The project aimed to create a skin cancer detection CNN model that can classify skin cancer kinds of an aid in early detection. [6]The dataset from the International Skin Imaging Collaboration (ISIC) challenge archives was used to train the model. If pollution continues to deplete the ozone layer, the number of skin cancer patients will rise.[7] Early detection is critical for skin cancer patients. In the image database, the back-propagation neural network classifier had an accuracy of 89.9% while the auto-associative neural network had an accuracy of 80.80%. Non-invasive medical computer vision or medical image processing is becoming increasingly important in the clinical diagnosis of many disorders. These techniques give an automatic image analysis tool for an accurate and quick assessment of the lesion.[8] The results show that the categorization accuracy achieved is 92.1%.

This paper suggested an artificial skin cancer diagnosis system where features of the damaged skins were extracted using the feature extraction technique after the dermoscopic pictures were segmented. [9]The retrieved features were stratified using CNN classifier. After using the publicy accessible dataset, an accuracy of 89.5% was obtained.The paper[10] suggests a DenseNet-based model to identify images more successfully than other classifiers, with training accuracy of 99.25% and testing accuracy of 100%. The DenseNet-based model produced state-of-the-art performance that can be used in both sectors and factories.

In this paper,[11] the analysis showed that preprocessing methods with KNN classifiers gave the best performance with accuracy of 93.103%. In this research,[12] authors have described the classification of skin lesions using PSO-based feature optimization. The suggested PSO model incorporated a variety of alternate velocity updating algorithms.The study proposes an early skin detection technique. The system distinguishes Malignant Melanoma from other skin conditions by utilizing Digital Image Processing Techniques and Artificial Neural Networks.[13] The accuracy of this system can be increased by altering the image processing techniques and classifiers.

In this study [14]it was observed that when pre-processed images are used as inputs, the deep learning-based algorithms produce higher accuracy. Therefore, to increase classification performance, pre-processing methods such as noise reduction, hair removal, color standardization, intensity normalization, and lesion region trimming are suggested. In this paper [15] the researchers used Deep Learning Studio a Model Driven Architecture for Deep Learning.

They introduced the features of the DLS tool which achieved an AUC of 99.77% in detecting cancer cells from the images. The researchers in this project used GLCM feature extraction technique and RGB color feature for classification. [16]To improve the accuracy of the classification, the ANN was optimized by genetic algorithm. The researchers used ECOC SVM and deep convolutional neural network. [17]Maximum values for average accuracy, sensitivity, and specificity were 95.1 (squamous cell carcinoma), 98.9 (actinic keratosis), and 94.17 (squamous cell carcinoma), respectively. The average minimum value in these measurements was 91.8 (basal cell carcinoma), 96.9 (squamous cell carcinoma), and 90.74 (melanoma). Here,[18] the researchers found that combining the inception module and residual blocks with a typical CNN model, GoogLeNet and ResNet achieved higher accuracy than stacking the same construction blocks again.

In this paper,[19] researchers introduced a unique graph-based pigment network detection approach that can locate and visualize pigment network round shapes gaining the accuracy of 92.6%. In this study,[20] a deep convolutional neural network-based spatial information extraction strategy is created as a tool for skin cancer classification. The experiment gave an accuracy of about 93.29%.

III. METHODOLOGY

Knowledge Discovery in Databases.
We have used Knowledge Discovery in database process for our project. It is a iterative process and mainly emphasizes finding knowledge from data. As shown in figure 1 the flow of KDD.

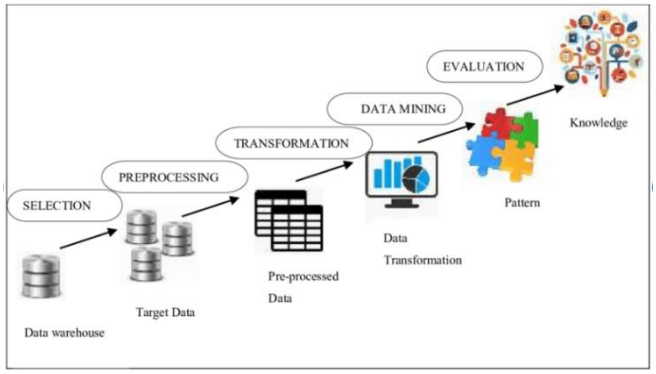

Figure 1 : Knowledge Discovery in Database

A. *Data Understanding*

The dataset was taken from Harvard Dataverse. The dataset contains large collection of multi-source dermatoscopic images of skin lesions. The dataset contains 10015 dermatoscopic images which includes the following categories of pigmented lesions: basal cell carcinomia(bcc), benign keratosis-like lesions(bkl), melanoma (mel) , Actinic keratoese and intraepithelial carcinoma (akiec) , dermatofibroma (df), vascular lesions (vasc) and melanocytic nevi (nv). The data was provided in 2 zipped files containing 5000 jpeg and 5015 jpeg files.

B. *Exploratory Data Analysis*

As the excel file has been loaded to Juypter, As shown in fig shows the image type distribution according to the lesion type, where we have a good amount of melanocytic nevi

images and other lesions are very few in number as consider to melanocytic nevi
As shown in Figure 2 the number of lesions per type for training directory and as shown in figure 3 the number of lesions per type for validation directory.

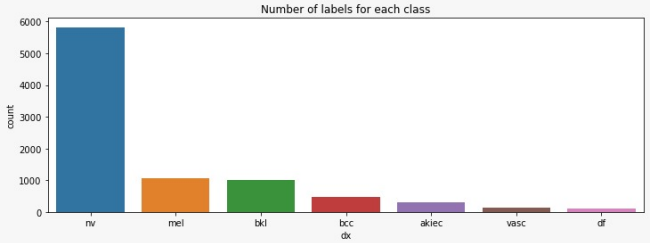

Figure 2 : Number of skin lesions per type for training directory

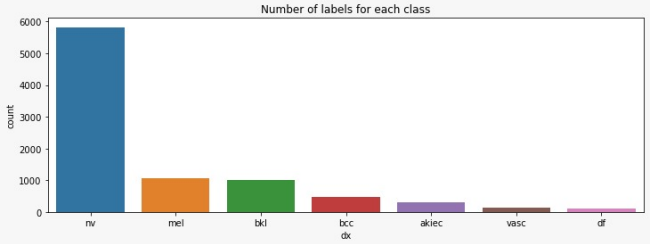

Figure 3: Number of skin lesions per type for validation directory

C. Data Preparation

The data was downloaded as archived files and then unzipped on system for later to be loaded through python. For start of data preparation All the libraries required for the project were imported, like tensorflow, keras, pandas, numpy etc. We have created a base directory in which 2 more directory were created:- train_directory and validation directory. Inside these both directory, seven directories were created according to the lesions we have. The directory names are :- "nv"," mel"," bkl"," bcc", "akiec", "vasc" and "df". In the archive, a metadata excel file was provided to understand the images better. The metadata file was loaded into Jupyter using python – pandas library. As lesion_id was an unique id number provided to all images, With use of lesion_id we had count the number of unique images that were 5514. As the data may contain duplicate images and need to remove those. We had checked the number of duplicate i.e 4501 and number of unique images i.e 5514. We had dropped all the duplicate values. Now data was cleaned and ready for further processing

D. Data Split into Train and Test:

Then we had created validation dataset with test size of 20% of dataset. The size of validation dataset was 1103. After this training dataset was created of which all images in validation set were excluded so there won't be any ambiguity. Once the train and validation set were created, we have checked the number of images per lesion in each dataset as shown in below figure 3 and Figure 4

```
Number of images in the Train Set =  8912

nv       5822
mel      1067
bkl      1011
bcc       479
akiec     297
vasc      129
df        107
Name: dx, dtype: int64
```

Figure 4 : Number of images of training dataset

```
Number of images in the Validation Set =  1103

nv       883
bkl       88
mel       46
bcc       35
akiec     30
vasc      13
df         8
Name: dx, dtype: int64
```

Figure 5 :Number of images of Validation dataset

Sorting Images into Test and Train Directories: -
As image list from excel was divided into train and validation, the images need to be also divided according to the Image_id (Lesion_id). Both the image folders were loaded into jupyter using python OS library and listdir function. We had created a loop for matching the image with the image list which was created earlier, to segregate them into train folder and validation folder. Once the images were moved to respective folder, we also did check the number of files in each directory to cross verify.

E. Data Augmentation

The ImageDataGenerator was used for data augmentation. There are many parameters which can be used, but we have used the following arguments: -

- rescale = 1./255 - it multiples the data by value provided.
- Shear_range = 0.2, it is shear intensity i.e shear angle in counter clockwise direction in degrees, Zoom _ange is 0.2 , It's a range for random zoom
- horizontal_flip =True, if true rotates the image to horizontal

The ImageDataGenerator class has three methods flow(), flow_from_dataframe and flow_from_directory() to read images from numpy array and folders containing images.
We have used flow_from_directory with the following parameters.

- First, we have given the path of the train directory
- Target size = (64,64) - it is the size of your input image; each image is resized to the value given here.
- Batch size = 32 – It is number of images to yield from the generator per batch

- Class mode – It has 2 values binary and categorical. If we have 2 classes to predict we can go with binary but since we have multiple, we have set to categorical.

The same was performed for validation directory with same parameters

F. Model Building

Convolutional Neural Network (CNN):-

Convolutional Neural Network is one of the most popular deep learning methods which is used to analyze visual images. CNN is composed of multiple layers of artificial neurons (these imitate as biological neurons). The artificial neuron's function is to calculate the weighted sum of multiple input and outputs an activation value. As shown in Figure 5 is the formula for Convolution Layer

$$W_{out} = \frac{W - F + 2P}{S} + 1$$

Formula for Convolution Layer

Figure 6: Convolution Layer formula

The below mentioned are the layers of model

- ❖ Conv2D : It created a convolution layers with multiple argument. The arguments passed were:-
  - Filters = 32
  - Kernel_size =3 , It is the dimension of the kernel, The parameter value should be odd integer
  - Activation = 'relu' , It is the activation function which we want to apply after performing convolution
  - Relu is easy to compute and offers predictable gradient for error backpropagation

- ❖ Pooling Layer:- It is responsible for reducing the spatial size of the feature, in simple words By reducing the dimensions of image, it decreases the computational power required to process the data. There are two types:- Average pooling and Max pooling
  - Average pooling – In the portion of image covered by the kernel an average of all the values is return. It performs dimensionality reduction.
  - Max pooling – It find the maximum value of pixel from the image portion covered by kernel. It performs as a Noise Suppressant (Discards noisy activations along with dimension reduction). Therefore, we have used Max pooling.
- ❖ Flatten – Flattening is used to convert all the resultant 2D arrays from pooled feature into a long continuous linear vector.
- ❖ Dropout layer:- It nullifies the contribution of some neurons towards the next layer to prevent overfitting on the data.
- ❖ Dense Layer – It is works for changing the dimensions of the output by performing matrix vector multiplication. It is a deeply connected layer from its preceding layer. The final dense layer contains softmax as activation function – as softmax converts a vector of value into a probability distribution.

Our model is a sequential model, where we have 2 convolutional layer, 2 Max Polling layer, 2 dropout layer 1 flattening layer and 2 Dense layers. The sequence of layers is shown in figure 5

```
cnn.summary()
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 62, 62, 32)        896

max_pooling2d (MaxPooling2D  (None, 31, 31, 32)        0
)

dropout (Dropout)            (None, 31, 31, 32)        0

conv2d_1 (Conv2D)            (None, 29, 29, 32)        9248

dropout_1 (Dropout)          (None, 29, 29, 32)        0

max_pooling2d_1 (MaxPooling  (None, 14, 14, 32)        0
2D)

flatten (Flatten)            (None, 6272)              0

dense (Dense)                (None, 1024)              6423552

dense_1 (Dense)              (None, 7)                 7175

=================================================================
Total params: 6,440,871
Trainable params: 6,440,871
Non-trainable params: 0
_________________________________________________________________
```

Figure 7 : Convolution neural network model summary

Then we have compiled the CNN model where the parameters are as follows: -

- Optimizer = adam – Adam Optimizer is a Stochastic Gradient descent method based on estimation of first order and second order
- Loss = categorical_crossentropy – it is used to compute the quantity that model should seek to minimize the traning. The catrgorical_crossentropy computes the crossentropy loss between the prediction and label.
- Metric = accuracy it is the accuracy how the model performs

The model was fit to the training and validation data set with 100 epochs. The Figure 6 shows the diagrammatically representation of our CNN model.

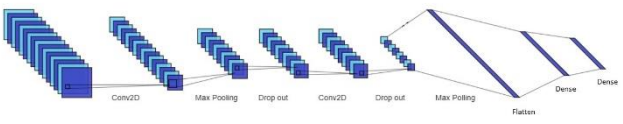

Figure 8 : Model diagram representation

As shown in Figure 7 , When we had executed the CNN model at start the accuracy was 0.8571 i.e 85.71%

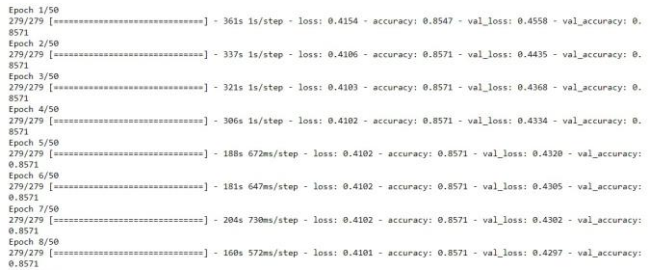

Figure 9 : Model Output at Start

As shown in figure 7 – the accuracy of model is 0.9727 i.e 97.27% and validation accuracy is 0.8540 i.e 85.40%

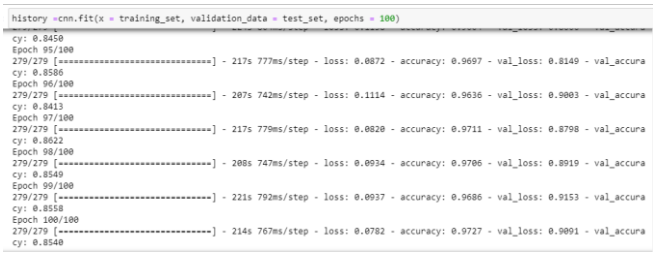

Figure 10 : Model Output

IV. Results and Evaluation

As a result, the model has given 97.27% % of accuracy to the model for classifying the skin lesion images.
As shown in figure 8, It shows the training and Validation accuracy, where the blue line shows the training accuracy and the orange line shows the validation accuracy , while on x axis is the epochs and y is the accuracy

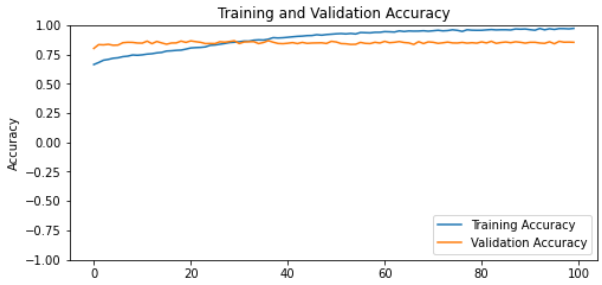

Figure 11 : Training and Validation Accuracy

As shown in the figure 9 the Training and the validation loss, with respect to epochs and loss – cross entropy. Also we can see the training loss is going down over the time by achieving low error values, but the validation loss had gone down until a turning point and started going up, which represents the overfitting beginning.

Figure 12 : Training and Validation Loss

V. Conclusions and Future Work

In this project we have applied Convolution neural network which yields a good result with 97.27% Accuracy. The layers and parameters passed in the model has worked very well. There was an overfitting issue with training and validation error loss, which would have been handled better by making the aligned layers of model in better sequence.
There is a room for improvement, where we can consider applying a different neural network with better modelled layers and parameters. Also, if the dataset can contain more lesion samples with good skin sample to be classify and the lesion type to be distributed equally so model can obtain a good understanding of each type and obtain better results

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