Image Classification of Skin Lesions

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***Abstract*— Skin cancer has always been a major issue of concern. It often begins with a small change to the skin. This cancer can be benign or malignant. The benign type is a common type of skin cancer that is developed on the top of the skin with a very less growth rate. Whereas malignant which is the most serious type of cancer with a high growth rate. Early detection of skin cancer can help to provide better success in treatment and hence can lower the death ratio. The proposed model will classify the skin lesion into seven categories that are Benign keratosis-like lesions, Dermatofibroma, Melanoma, Vascular lesions, Basal cell carcinoma, Melanocytic nevi, Actinic keratoses, and also detect whether the given skin lesion is a benign type of cancer or malignant. The dataset used in the experiment is HAM10000(Human Against Machine 10000 training image) dataset. There is two classification model used in this experiment. The first model is discovered using AutoKeras which will discover an effective neural network for the provided dataset. The second model is InceptionResNetV2, which is a pre-trained neural network. Both the model has good accuracy so this depicts that the neural network is perfectly suitable for skin lesions classification.**

***Index Terms*—AutoKera, HAM10000, InceptionResNetV2, U-Net**

I. Introduction

Skin cancer is the most commonly seen cancer worldwide. It has been reported that more than 207,000 cases of melanoma were diagnosed by doctors in 2021. Melanoma skin cancer is considered the deadliest type of cancer. Another study says that one person in every five develops benign skin cancer by the age of seventy and this risk keeps on increasing after that age. Mainly skin cancer is caused due to exposure to sunlight which has harsh and harmful UV rays which damage the skin cell and result in skin cancer. It is usually seen as a new spot or change on the skin. This change on the skin can either appear as a mole, patches, or unhealing pimples or lesions on the surface of the skin. Signs of skin cancer are a suddenly appearing spot on the skin that keeps on increasing with time or a mole that keeps on increasing etc. Skin cancers are extremely treatable if detected at an early stage. Kowing the signs of skin cancer is the key to early identification.

Previously, features of images were extracted manually from the affected area using many images pre-processing and manual segmentation and then fed to a traditional classifier [1]. The due growing use of deep learning in the medical field has resulted in the creation of a number of promising classification models like Convolutional neural networks etc. [2]. Extraction of features from the image and its classification are studied and performed as a single method. Lee et al., [3], have done work with the combination of U-Net and DenseNet model for segmentation of image and ensemble of classifier to provide a great accuracy of 78.9%.

Here HAM1000 dataset is used to training and classification purpose. HAM10000 dataset which is termed as Human against machine with 10000 images is a large dataset consisting of 10000 dermatoscopic images which are released for training machine learning models. Method involved is data preprocessing, Exploration of data ,Label encoding, Data Augmentation ,Balancing the data set and then define classification model (neural network model provided Autokeras and a pretrained model InceptionResNetV2).

In literature reviews, there were several approaches taken for classifying skin lesions. But most of those approaches have problems such as missing test results with enormous data, limited performance, and heavy-weight models. We provide a novel approach to bypassing this limitation in this work.

II. Dataset Preparation

A. Data Pre-Processing and Data Cleaning

Data preprocessing is the manipulation of the dataset before using it so that it can increase its performance. Here, from Fig.1 we can see that the provided HAM10000 data has column image_id,cell_type ,is_benign, and localization column is not in use. So, in this Pre-processing step, we are dropping this column.

	image_id	cell_type	is_benign	localization
0	ISIC_0027419	Benign keratosis-like lesions	1.0	scalp
1	ISIC_0026769	Benign keratosis-like lesions	1.0	scalp
2	ISIC_0031633	Benign keratosis-like lesions	1.0	ear
3	ISIC_0029176	Benign keratosis-like lesions	1.0	face
4	ISIC_0029068	Benign keratosis-like lesions	1.0	face

Fig. 1. HAM10000 dataset

The next, step is to remove all the null values from the column which is in use. “dropna” function will remove all the null values from the dataset. The next step is to check the data type of the column as is_benign column is

given in float data type, so it has to be converted into int as it contains values of 0 and 1.

B. *Exploratory Data Analysis*

Here in this step a dataset is analyzed and summarized using data visualization tools like graphs and charts. So here firstly we will be encoding labels from cell_type column into numbers. This will help while training the model. Because training is done against images with this encoded numbered label. We are using “LabelEncoder” to do so.

	image_id	cell_type	is_benign	label
8	ISIC_0025915	Benign keratosis-like lesions	1	2
4758	ISIC_0032523	Melanocytic nevi	1	4
3809	ISIC_0033698	Melanocytic nevi	1	4

Fig. 2. Label Encoded Dataset

After Encoding labels to Numbers, the next step is to visualize the dataset to study the distribution of data. Bar char is used to visualize cell_type column against image count and is_benign column against image count. Here we observed that data is unevenly distributed which is making the dataset highly imbalanced. Given below graph represent the data distribution of seven categories of column "cell_type". Graphs show that the dataset is not balanced as 'Melanocytic nevi' has a very large no of volume (3527) as compared to other classes and also 'Dermatofibroma'(61) and 'Vascular lesions' (71) are very less as compared to class 'Melanocytic nevi' and other classes.

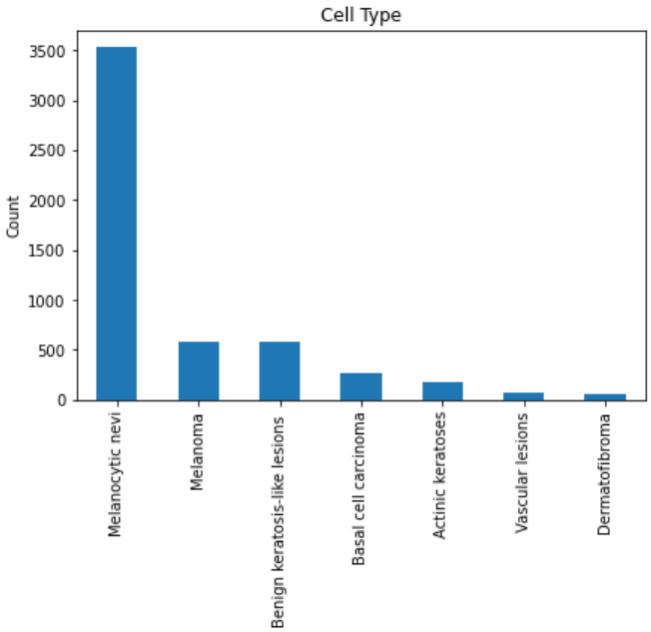

Figure 3 Bar Chart of Image count of each Cell Type

The next step is to balance the dataset, it can also be done while training. First, we are separating each class value into a separate dataset. This will help us to augment them individually. Now we will resample each dataset from the above step. as we know that classes are not distributed equally to make them equal, we are resampling. we are using "resample" from "sklearn.utils" for this process. This will resample data of each class, we are choosing resampling data as 250, so it will upscale data of classes that have a lesser count of data than 250, and also it will bring down the data of classes which has a count of data more than 250. Now we will combine all the balanced datasets of all 7 classes into one single data frame name "skin_df_balanced".

As we are training the image against the label, so one more column is being added to the balanced dataset to extract all the paths of the image, so that in the Augmentation process it can be easily extracted.

C. *Data Augmentation*

In this process, each image opened from the path provided in the present in the "skin_df_balanced" dataset with respect to each image_id. Then each image is resized to (32*32) size and then each image is converted into numpy array and add it to a newly created column named image with respect to each image_id. The stored value of the image is stored in the form of pixels in the image column data frame. So it will be in the range of 0 to 255 as the minimum pixel value is zero and the maximum is 255. So in the below code, we are normalizing it to the scale of 0-1 by dividing by 255.

D. *Splitting of Dataset to Test and Train*

Here we will be splitting the balanced dataset on the basis of the image stored in the image column and label. Dataset is split using train_test_split() function with test size 25% which means 25% of the data set will be used for testing and the rest 75% will be used for training the model. Here we have assigned the image to ‘X’ and label to ‘Y’ .

III. METHODS

Here we are using two separate methods for classifying the following features:

1. a skin lesion is benign or malign.
2. classification into seven categories of cell type.

First Method

For the first method, AutoKeras is being used. AutoKeras has a user-friendly interface for a range of tasks such as picture classification, structured data categorization, and regression. Simply specify the location of the data as well as the number of models to test, and the model with the best performance on that dataset will be returned. As it has many neural network so it will provide a greater accuracy .

Second Method

Here we are using a pre-trained neural network i.e. InceptionResNetV2 for the classification image. This model has already been trained using a large image dataset previously which has many features of the training dataset, hence it has all those weights and biases which can help in improving the accuracy of the classification. ResNet and

Inception have been key to recent breakthroughs in image recognition performance, offering excellent results at a cheap computational cost.

IV. EXPERIMENT AND EVALUATION

A. *EXPERIMENT*

for the First Method we are using AutoKeras to find the best neural network for this particular dataset. AutoKeras is an open-source library for deep learning models that performs AutoML. The discovery is carried out using Keras models and the TensorFlow tf.keras API. So Here 25, the trial was done on different models by AutoKeras and the best one among that was taken for doing this task. So now we have to define the suggested model by AutoKeras. This Model has 7 dense layers. The output of Each layer is fed to the next successive layers.

Next is the training of the model with the trained dataset. Here we are assigning batch sizes as 16 and epochs as 50. We are using model.fit() to fit data set with defined model. In this method both of the features are trained and classified separately. Firstly, images are trained against labels to predict label. For predicting benign and malignant, images are trained against the "is_benign" column.

For the second method we are using a pre-trained neural network i.e. InceptionResNetV2 for the classification image. This shows a benchmark accuracy rate, as it already has been trained, we are again training the model with respect to our data so, it will provide more accuracy. we are same model to classify both features. We have provided the input shape and weight as magnet. And then the model is trained with data set using fit_generator.

B. *EVALUATION*

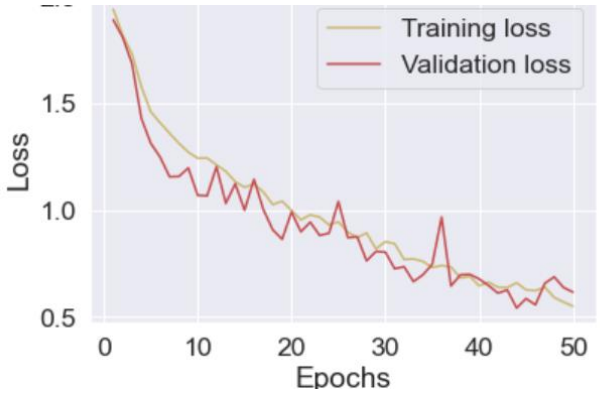

Fig. 4. Training and validation loss of classification into seven categories of cell type using neural network by method 1.

Model one is showing accuracy rate of 89 % for classification of images into seven cell type .

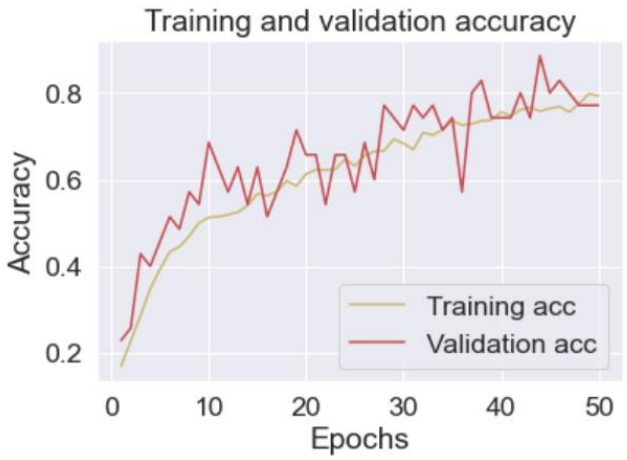

Fig. 5 . Training and validation accuracy of classification into seven categories of cell type using the neural network by method1.

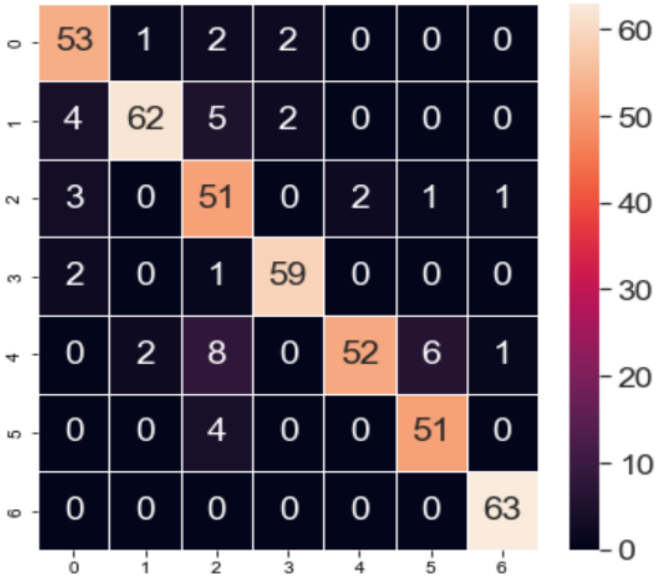

Fig. 6. Confusion matrix of Predicted vs True

Model one shows an accuracy rate of 76 % for the prediction of benign and malignant .

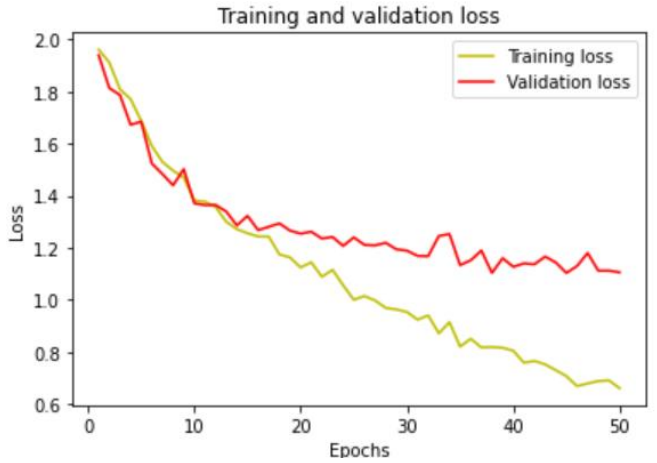

Fig.7. training vs validation loss of Prediction of benign and malignant cancer using the first method

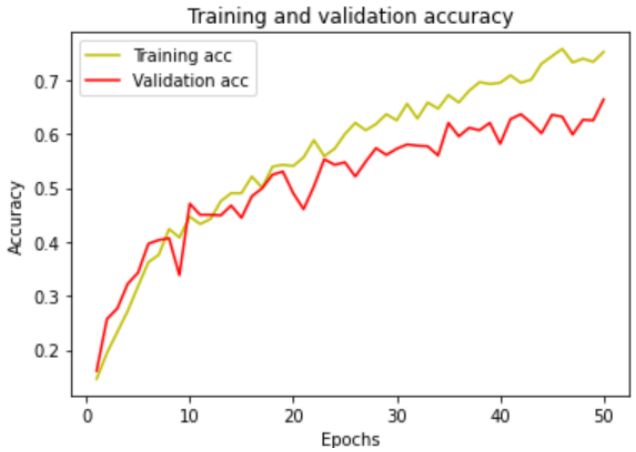

Fig. 8. Training vs validation accuracy of Prediction of benign and malignant cancer using the first method.

InceptionResNetV2 is showing an accuracy of approximately 77.98 for the classification of images as benign and malignant

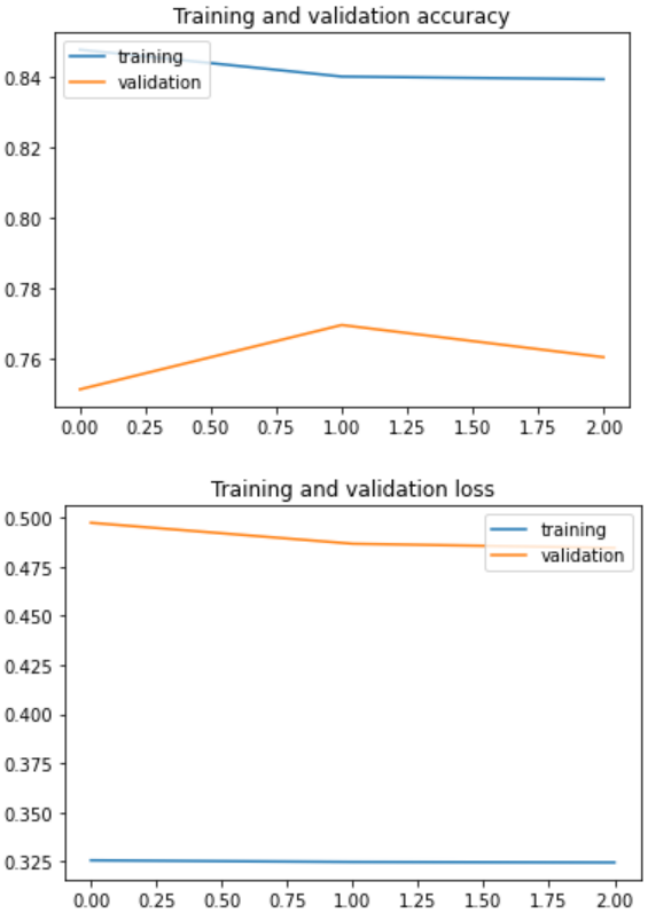

Fig. 9. Training vs validation loss and validation accuracy of classification of cell type into seven types using InceptionResNetV2

InceptionResNetV2 is showing an accuracy of approximately 88% for the classification of images into seven categories according to the cell type.

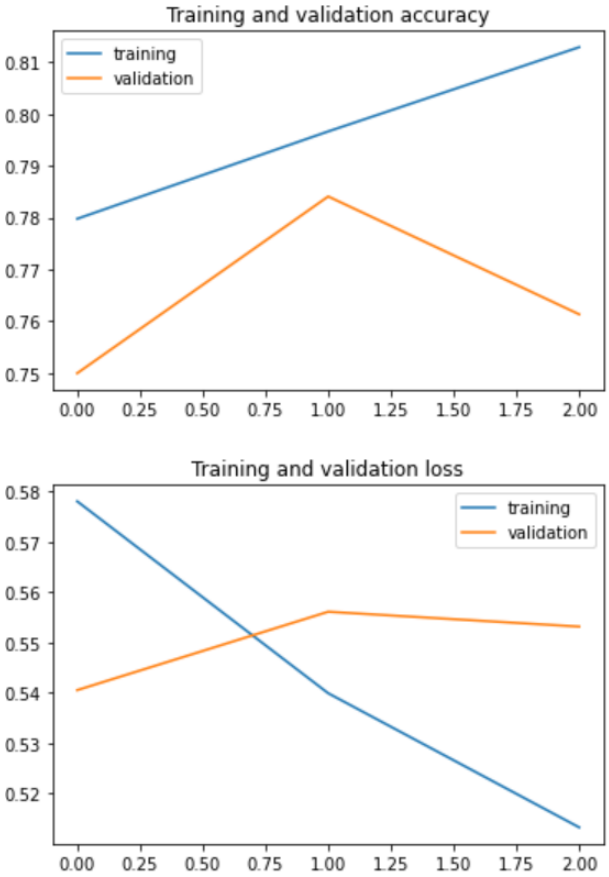

Figure 10 Training vs validation accuracy and loss of classifying images into seven categories of the cell type used InceptionResNetV2

V. DISCUSSION AND FUTURE WORK

From the evaluation, we can see that the pre-trained model has more accuracy than the method one neural network predicted by AutoKeras. And validation loss is also comparatively lesser in the InceptionResNetV2 model. As it is already so it will provide more accuracy than model one. I would prefer InceptionResNetV2 over the first neural network. The dataset may be expanded to use all of the images from the original dataset for better prediction. The results show that, while the ensemble model works well, there is still scope for improvement.

VI. CONCLUSION

Diagnosis of skin pathology is a challenging approach that takes time and may result in a mistake. As a result, automated systems based on machine learning are critical tools for supporting doctors in properly categorizing skin lesions. The proposed system consists of four major phases: data pre-processing and data cleaning, exploratory data analysis, splitting into training and testing dataset, defining the required model, and training the model (image against required images). The code is run on a jupyter notebook and the classification model is based on a neural network. Here we have used two classification models one is suggested by AutoKeras and the

other one is InceptionResNetV2 which is a pre-trained model. The system is demonstrated, with data visualization as the statistical criteria used for categorization. The method achieved an accuracy of roughly 76 to 88 percent. In the future, the system can be improved by using ensemble learning approaches or evolutionary algorithms, which promise even higher accuracy and faster outcomes.

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