SKIN CANCER DETECTION USING DEEP LEARNING

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ABSTRACT

Human skin is the most exposed part of the human body which needs to be prevented from heat, light, dust and direct exposure to UV rays. Skin cancer is one of the dangerous diseases found recent days. The higher damage caused by the skin cancer is mostly due to the late identification of it. Some of the challenges that affects the success of skin cancer detection include small datasets or data scarcity problem, noisy data, imbalanced data, inconsistency in image sizes and resolutions, unavailability of data, reliability of labelled data and imbalance of skin cancer datasets. This content provides a data augmentation technique based on Synthetic Minority Oversampling Technique (SMOTE) to address the class imbalance problem in the given images. Then it is a challenging task to distinguish between malignant and benign skin lesions as they are alike in their physical appearances. This results in more unnecessary biopsies. To tackle this problem, we developed an enhanced image classification model which can act as a preliminary check before moving to a costlier biopsy. The proposed model can recognize 7 distinct types of skin lesions. Analyses have been performed on the HAM10000 dataset. The classification process is based on transfer learning using multiple pre-trained models, combined with class-weighted loss and augmentation of the data. Experimental analysis shows that the modified ResNet50 model is capable of identifying skin lesion images into one of the seven classes of image.

Keyword: *HAM10000, Skin cancer, types of cancer, RESNET-50, SMOTE, Sampling, detection.*

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1. INTRODUCTION

Skin cancer the abnormal growth of skin cells most often develops on skin exposed to the sun. But this common form of cancer can also occur on areas of your skin not ordinarily exposed to sunlight. There are three major types of skin cancer - basal cell carcinoma, squamous cell carcinoma and melanoma. You can reduce your risk of skin cancer by limiting or avoiding exposure to ultraviolet (UV) radiation. Checking your skin for suspicious changes can help detect skin cancer at its earliest stages. Early detection of skin cancer gives you the greatest chance for successful skin cancer treatment.

This proposed system is provided to early detect the types of the skin cancer. The proposed system provides the detection the skin cancer type using the deep learning concept. The provided system is functions by giving the images to the model to train and predict the type in future. The concept is established as by the prior prediction of the of the type of skin cancer the diagnosis for the cancer is done perfectly. The dataset used is the HAMSET10000.

HAM10000 is a dataset of 10000 training images for detecting pigmented skin lesions. The authors collected dermatoscopic images from different populations, acquired and stored by different modalities. The provided data can be used for the further researches the research which are done are the skin lesion detection uses. All the custom provided images can be used to train and test the model.

In most of the images classification technique the deformity is, misjudged and the types cannot be found this leads to a very huge harm providing matters. Some types of the skin cancer puts the risk to life without providing a simple classification and verification.

The proposed system classifies and also provide the cancer diagnosis accurately. The early proposed systems have the issues such as providing with less accuracy and also types cannot be mentioned only melanoma is mentioned all over. This proposed system uses the SMOTE for the image imbalance reduction purpose and preprocess the image size and provide the proper contrasted images for validation and the ResNet-50 architecture of transfer learning with the pre-trained model using the ImageNet. This method will provide best accuracy over the prediction of the types of skin cancer present.

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Fig1.1: Types of skin cancers

2. RELATED WORKS

The previous process and systems provide us a knowledge for us to create a proper system. Classification layers of these individual CNNs, and interconnect them with inserting a joint fully connected layer followed by the classic SoftMax/classification layers for the final prediction.[1]. Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available datasets of dermatoscopic images. We tackle this problem by releasing the HAM10000 ("Human Against Machine with 10000 training images") dataset. We collected dermatoscopic images from different populations acquired and stored by different modalities. This benchmark dataset can be used for machine learning and for comparisons with human experts [7]. Another proposed model has a good pre-processor that classifies the skin lesion without much difficulty. The mean RGB have been removed and image is resized so it can be predicted accurately with the help of classifiers such as Resnet classifiers [2]. Imbalanced class data distribution occurs when the number of examples representing one class is much lower than others. This conditioning affects the prediction accuracy degraded on minority data. To overcome this problem, Synthetic Minority Oversampling Technique (SMOTE) is a pioneer oversampling method in the research community for imbalanced classification. The basic idea of SMOTE is oversampled by creating a synthetic instance in feature space formed by the instance and its K-nearest neighbors due to the ability to avoid overfitting and assist the classifier in finding decision boundaries between classes [8]. The extraction of image with reduced noise, hair and air bubbles. This will increase the image accuracy with computer automated technique along with CNN that uses SVM. The identification of melanoma skin lesion is found with better accuracy [3]. The main advantage of using this method is to classify whether its melanoma cancer or non-melanoma cancer tissue. That is why in deep learning we use ImageNet to classify the skin segments. With the help of augmentation, we get to see the lesion in all the angles like 0-270 degrees [4]. The method in one advance it uses RCNN to find the melanoma cancer lesion. It also does not need to be fed manually and it has been trained over 900 training images, this method provides a very good accuracy of 93% with larger dataset [5]. The major success of this model is that it removes unwanted noises and sound from the images. The accuracy has been improved well with the help of Resnet 34. It can classify layer up to 34 and see the details clearly. This model also has speed compared to other deep learning methods and provides a better accuracy [6]. These are the process identified in the system which are applied in system.

3. EXISTING SYSTEM

The existing system uses ISIC 2019 data set images. They can classify several skin cancers tissues. The classification of images the dataset is complicated. Pre-processing technique is not well applied so it affects the accuracy of the system. It uses Region based CNN method with ResNet-34 algorithm, which is a very basic kind of algorithm of ResNet. The overall system doesn't provide a proper system for the image processing method, it only comprises the image dimensions and things. There a very least amount of depth layer is been used over the system. They can provide an accuracy of around 92% only.

4. PROPOSED SYSTEM

The proposed system uses Transfer learning method, which is basically we pretrain an model with bunch of datasets and it will used to predict the types of skin lesions. Here we use Hamset10000 datasets which has 10015 images to identify the type of cancer tissue. We use ResNet50 model to see the skin lesion with more accuracy. The system follows the CNN architecture with Adam optimizer for the optimizing purpose. The fig 4.1 refers the process which are being processed. Using the help of this transfer learning concept we would be able to produce accuracy of above 93%. We can able to find various skin cancer tissues compared to old system. There are several modules and technologies which are implemented together for the system to function.

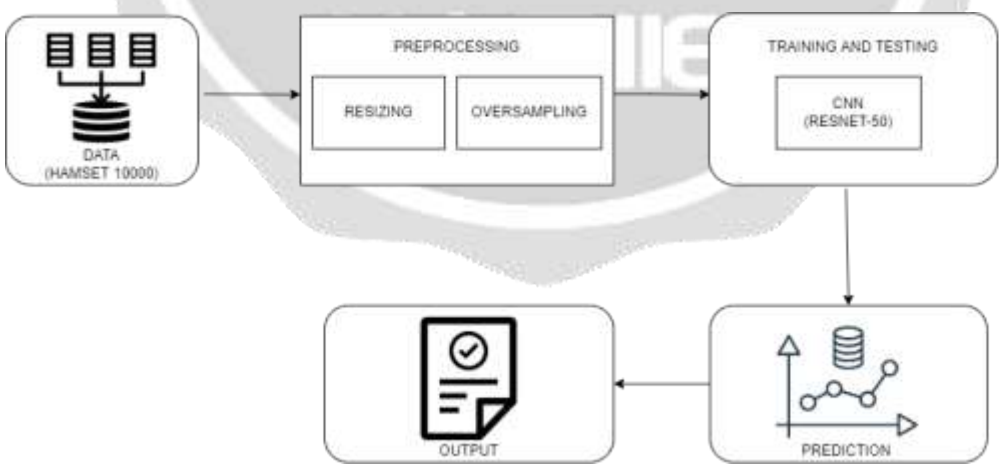

Fig 4.1: Process flow

4.1 Preprocessing :

Preprocessing is the process which is basically performed before using the data in the dataset to train the model. Data such as images which are used in the deep learning are basically imbalanced and vary over one another. To avoid this kind of data imbalance the preprocessing method is performed basically. Data labelling is done over the process of preprocessing for the to identify the data provided within the dataset. Labelling makes the process of comparing and identifying the types of skin cancer. Similarly resizing is also done to make the image pixel provided in the data set to be similar. SMOTE is a preprocessing technique used for balancing the data before its been proceeded to training. SMOTE (synthetic minority oversampling technique) is one of the technique used for oversampling . That is used to solve the imbalance in the class. It aims to balance class distribution by randomly increasing minority class examples by replicating them. In this skin cancer detection we also use SMOTE to avoid the class imbalance in the datasets.

4.2 Training and Testing :

The preprocessed data is implied into the CNN architecture model for processing the image and creating a model to predict the output. The CNN architecture which is used for the training and testing process is the ResNet-50. The ResNet-50 contains 50 deep layers in the structure, where there is 48 convolutional layers ,1 Max Pool layer and 1 Global Average Pool layer. Global Average Pooling is a pooling operation designed to replace fully connected layers in classical CNNs. The model uses 9,013 images for the training process and 1002 images for the testing process. With this amount of data we perform the pre-trained model for the prediction process. The Adam optimizer is used in the algorithm for the optimizing purpose. It change the attributes of the neural network such as weights and learning rate to reduce the losses. This algorithm is used to accelerate the gradient descent algorithm by taking into consideration the 'exponentially weighted average' of the gradients. The provided model with the proper accuracy is saved in the a file and the model is saved for the further prediction result. These are the major process takes place over this model.

4.3 Prediction :

This module uses the saved model in the training and testing process. The prediction module does the process of predicting the input by using the saved model. The model trained contains the seven types of skin cancers, which is used for comparison and identification. The GUI is build using the python using the tkinter library files with the prediction process within it. The GUI has the buttons which are used to process the prediction of the system. The system has the process which gathers the input files from the system, which are mostly the image of a skin cancer. By getting the input file the system will predict and will produce the output by providing the name of the cancer type. This is the major process of the GUI which has the final outcome and result. The input image is sized properly and the model is used to compare the input image with the trained model. The system will process the input image with the cv file of data and it will help to produce the output.

Fig 4.3.1: Input the image

As mentioned in the process in Fig 4.3.1 the sample image input is provided into the system. Once the input is provided the image is processed and it is predicted. The example can be found in the Fig 4.3.2 where the result is displayed as the type of skin cancer.

Fig 4.3.2: Display the result

5. RESULT AND DISCUSSION

Various methods were used to identify the skin cancer tissue. They had its own pros and cons . One of the issue we had in existing system was that we were able to find the cancer tissue in early or in prostate time. The problem was we were not able to tell which type of cancer it was found. In another system we were able to find only 4 or less types of cancer tissue with less accuracy compared with the proposed system. The proposed system can tell seven types of cancer tissue with better accuracy.

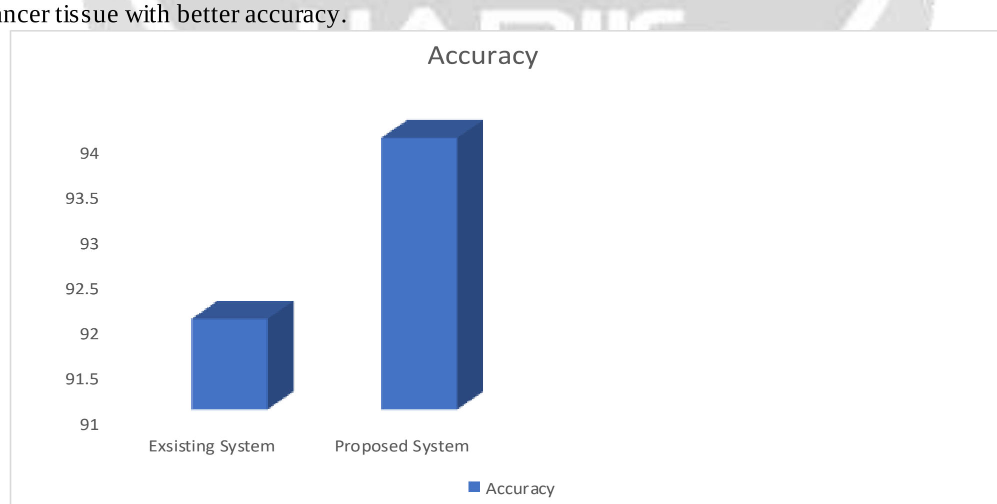

Fig 5.1: Comparison graph

Resnet-50 is the architecture used in CNN algorithm. The previous model used Resnet-34 but it was comparatively lower version of it. The number images pretrained is in much larger scale compared to Resnet -34. Both the architecture does training in RGB order. The main difference is that resnet-50 does classification much deeper with 50 layers. The existing system uses Resnet-34 and able to provide accuracy almost 92%. The another existing system they have only image classification and it takes lot of time to pre-process. CNN is much more easier and accurate in image pre-processing. ANN have been used in previous model as part of detecting the cancer tissue and CNN proves to be much more accurate. The training in deep learning may take lot of time but once its been trained the result will be predicted in less time. This is based on the pre trained models, so with many images enough training will be given.

6. CONCLUSION AND FUTURE ENCHANCEMENT :

This project as specified is finding the Skin lesions on the person. Compared with previous models this allows us to gather many datasets and does a training for long time. This helps in balancing the datasets. Previous model haven't been used a technique like this, only a traditional image classification method was used. We use Resnet-50 architecture to deeply classify the images. Finally we display the result in the GUI format. For this we import library files from Tkinter. Thus the overall model is based on Deep learning method and it gives us a accuracy of 93.66%.

This project will be very useful in medical industry. It helps in identifying the problems a person faces with skin tissues. Many have suffered skin cancer due to late identification. With help of this project, we can identify it at early stage. As this project is done with deep learning method, the result we get are more accurate. It gives hope in the field of oncology.

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