Skin Disease Detection using Convolutional Neural Network

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Abstract - *Dermatology remains one of the foremost branches of science that is uncertain and complicated because of the sheer number of diseases that affect the skin and the uncertainty surrounding their diagnosis. The variation in these diseases can be seen because of many environmental, geographical, and gene factors and also the human skin is considered one of the most uncertain and troublesome terrains particularly due to the presence of hair, its deviations in tone and other similar mitigating factors. Skin disease diagnosis at present includes a series of pathological laboratory tests for the identification of the correct disease and among them, cancers of the skin are some of the worst. Skin cancers can prove to be fatal, particularly if not treated at the initial stage. The Convolutional Neural Network system proposed in this paper aims at identifying seven skin cancers: Melanocytic Nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesions, and Dermatofibroma. The dataset used is "Skin Cancer MNSIT: HAM10000" and was obtained from Kaggle. It has a disproportionate number of images for each disease class, some have well over a thousand while others have a few hundreds.*

Key Words: **Dermatology, Skin Disease, Cancer, Convolutional Neural Network, MNSIT: HAM10000**

1. INTRODUCTION

Skin Cancers have wreaked havoc since the early ages and it is particularly because of the sheer number of cancers that are present that they pose such a high risk - It is difficult to diagnose them without a laboratory test. In our attempt to bring about a change in this ecosystem, we have proposed an automatic skin cancer classification system that can help people in identifying the particular type of pigmented lesion that has taken over their skin. The idea behind this project is to make it possible for a common man to get a sense of the disease affecting his/her skin so they can get a head start in preparing for its betterment and also the doctor in charge can get an idea about the type of cancer, which ultimately helps in faster and efficient diagnosis. We make use of a Convolutional Neural Network that uses Batch Normalization to normalize the layer's inputs and also makes use of an Adam optimizer. The dataset used is open source obtained from Kaggle and of all the lesions in the dataset, more than 50% has been confirmed through histopathology.

2. LITERATURE REVIEW

[1] Classification of skin cancer using CNN analysis of Raman Spectra.

The performance of convolutional neural networks is compared and also the projection on latent structures with discriminant analysis for discriminating carcinoma using the analysis of Raman spectra with a high autofluorescence background stimulated by a 785 nm laser. They've registered the spectra of 617 cases of skin neoplasms (615 patients, 70 melanomas, 122 basal cell carcinomas, 12 epithelial cell carcinomas and 413 benign tumors) in vivo with a conveyable Raman setup and created classification models both for convolutional neural networks and projection on latent structures approaches. To test the classification model's stability, a 10-fold cross-validation was performed for all created models. To avoid model overfitting, the info was divided into a training set (80% of spectral dataset) and a test set (20% of spectral dataset). The results for various classification tasks demonstrate that the convolutional neural networks significantly ($p<0.01$) outperforms the projection on latent structures.

[2] Channel Attention based Convolutional Network for skin disease classification.

This research aims to develop a system for detecting skin diseases employing a Convolution Neural Network (CNN). The proposed model named Eff2Net is constructed on EfficientNetV2 in conjunction with the Efficient Channel Attention (ECA) block. This research attempts to switch the quality Squeeze and Excitation (SE) block within the EfficientNetV2 architecture with the ECA block. By doing so, it had been observed that there was a big call for the full number of trainable parameters. The proposed CNN learnt around 16 M parameters to classify the disease, which is relatively less than the present deep learning approaches reported within the literature. This disease classification was performed on four classes: acne, keratosis (AK), melanoma, and psoriasis.

[3] The Automated skin lesion segmentation using attention based deep Convolutional Neural Network

To advance the digital process of segmentation, a deep learning-based end-to-end framework is proposed for automatic dermoscopic image segmentation. The framework has the modified kind of U-Net, which effectively uses Group Normalization (GN) within the encoder and also the decoder layers. Attention Gates (AG) that specializes in minute details within the skip connection, later incorporates Tversky Loss (TL) because the output loss function is added. Rather than Batch Normalization (BN), GN is employed to extract the feature maps generated by the encoding path efficiently. To tell apart high dimensional information from low-level irrelevant background regions within the input image, AGs are used. Tversky Index (TI)-based TL is applied to accomplish better alliance between recall and precision. To further strengthen feature propagation and encourage feature reuse, atrous convolutions are applied within the connecting bridge between the encoder path and therefore the decoder path of the network. The proposed model is evaluated on the ISIC 2018 image dataset.

[4] Deep learning approach to skin layer segmentation in inflammatory dermatoses

In practice, the analysis, including segmentation, is sometimes performed manually by the physician with all drawbacks of such an approach, e.g., extensive time consumption and lack of repeatability. Recently, HFUS has become common in dermatological practice, yet it's barely supported by the use of automated analysis tools. To satisfy the necessity for skin layer segmentation and measurement, they have developed an automatic segmentation method of both epidermis and SLEB layers. It consists of a fuzzy c-means clustering-based preprocessing step followed by a U-shaped convolutional neural network. The network employs batch normalization layers adjusting and scaling the activation to make the segmentation more robust. The obtained segmentation results are verified and compared to state-of-the-art methods addressing the skin layer segmentation. The obtained Dice coefficient adequate 0.87 and 0.83 for the epidermis and SLEB, respectively, proves the developed framework's efficiency, outperforming the opposite approaches.

[5] Skin cancer detection using Convolutional and Artificial Neural Networks

This paper focuses on the event of classifiers capable of detecting skin cancer(s) given dermoscopic images. The dataset used for the training is a part of the 2019 ISIC Challenge, and consists of over 25,000 labeled dermoscopic images. Specifically, classifying dermoscopic images accounts for nine different diagnostic categories: melanoma, melanocytic nevus, basal cell carcinoma, keratosis, benign keratosis, dermatofibroma, vascular lesion, and epithelial cell carcinoma, a number of which are benign. They've developed classifiers -a binary classifier and a multiclass classifier -on the Google Cloud Platform using Convolutional Neural Networks (CNNs). To forestall the classifiers from overfitting and to attain higher accuracy even with the smaller training data size, they've used image data augmentation. The binary classifier achieved an accuracy of 73% with 220 epochs of coaching, and therefore the multiclass classifier's accuracy is 72% with 200 epochs. Finally, the results are shown to the user, including the kind of disease, spread, and severity.

3. METHODOLOGY

We begin by resizing the images to 28,28 for better learning and then proceed to add the names and labels after which the plot parameters are set. The image pixels are stored as a dependent variable while the target label is stored as an independent feature. The data is divided into train and test split and it is reshaped to handle the imbalance issues (it can only be handled if the data is 2 Dimensional), after which Random Oversampler does the job of handling the imbalance. The data is fit on the train set and the new shape is checked, following which it is reshaped again to 3 Dimension in order to train the Convolutional Neural Network.

After checking if the shape is acceptable, the Convolutional Neural Network model is defined and subsequently the first layer of the CNN is plotted. Max pooling is used to select the maximum features as identified by the convolutional filter. After this, Batch Normalization does the job of making the Artificial Neural Network faster and more stable by normalization of the layer's inputs through re-scaling and re-centering. The Convolutional Neural Network is Flattened to feed the fully connected Artificial Neural Network and Dropout is used to avoid overfitting. After all this, the first Artificial Neural layer is defined. Softmax is used as the activation function to the output layer which has 7 neurons. For optimization, the learning rate is set to 0.001 and Adam optimizer is used.

The model is compiled with accuracy as metric and loss as Sparse categorical since we have multiple outputs and then after that the data is trained using sample validation split as 0.2. The model is predicted on the test set and the predicted probability is converted to classes. The model is then finally evaluated. The parameters amount to about half a million of which about a thousand are non-trainable params.

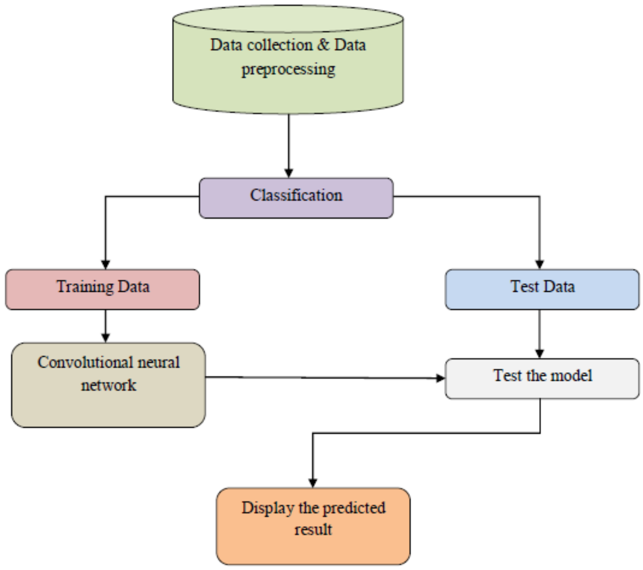

Fig -1: Data Flow diagram

The above figure represents how the data transitions into various stages as required for the prediction.

4. RESULTS

The system was seen to predict the said diseases with an accuracy of around 74% - 75%. The model loss can be seen decreasing abruptly at first and then gradually towards the end. Accordingly, the accuracy rises abruptly and consolidates towards the end. The epoch was set to 50 after carefully testing for different epoch values.

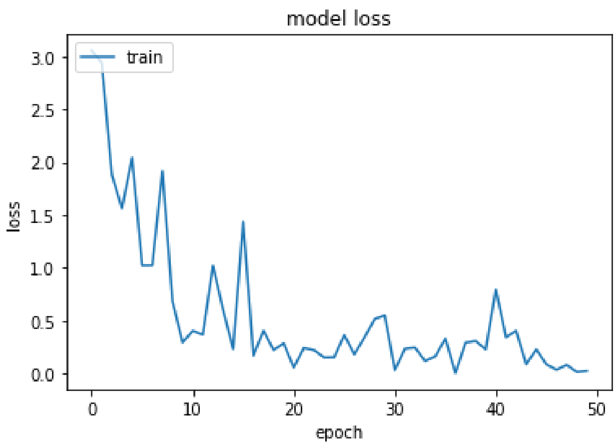

Chart -1: Model Loss Chart

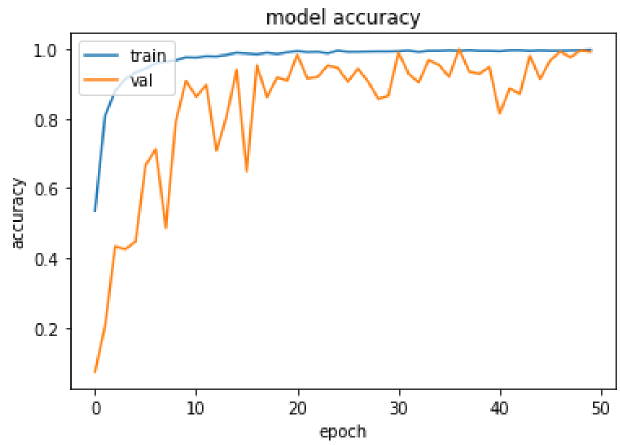

Chart -2: Model Accuracy Chart

The 2 graphs depict the decreasing model loss and the increasing accuracy of the system respectively.

5. CONCLUSION

We observe that the CNN model is accurate to an extent and going forward, with careful scrutiny and a more reliable dataset, the model can be tweaked to attain a greater degree of accuracy. By storing the results in an H5 file, one can build an application around it that could give quick predictions on the go to users who upload an image of the diseased part of their skin.

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