CNN BASED SKIN DISEASE PREDICTION

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Abstract –

Due to the diversity of skin illnesses and the difficulty in accurately diagnosing them, dermatology continues to rank high among the most uncertain and complex scientific disciplines. The human skin is one of the most uncertain and challenging terrains, especially owing to the existence of hair, its variances in tone, and other comparable mitigating variables, and the diversity in these disorders may be noticed because of numerous environmental, regional, and genetic factors. Cancers of the skin are among the most dangerous skin diseases and the current diagnostic process for them involves a battery of pathological laboratory testing. When not caught and treated early, skin malignancies have a very high mortality rate. These seven types of skin cancer are targeted by the Convolutional Neural Network method suggested in this paper: melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. The "Skin Cancer MNSIT: HAM10000" dataset from Kaggle was utilized for the analysis. Some illness categories contain over a thousand pictures, while others only have a few hundred.

1. INTRODUCTION

Because there are so many different types of skin cancer, they have been wreaking havoc since ancient times, and it is impossible to detect them without a lab test. To effect change in this environment, we have presented a method for automatically determining the sort of pigmented lesion that has spread over a person's skin, a.k.a. skin cancer. The goal of this project is to aid in the diagnosis of skin cancer by giving the average person some idea of the type of cancer he or she may be dealing with and giving the treating physician a head start in treating it. Our Convolutional Neural Network employs an Adam optimizer and Batch Normalization to standardize layer inputs. The dataset utilized is publicly available and was retrieved from Kaggle; more than half of the lesions in the dataset have been verified by histopathology.

2. LITERATURE REVIEW

[1] CNN analysis of Raman spectra for skin cancer classification.

The examination of Raman spectra with a strong auto fluorescence background produced by a 785 nm laser is used to distinguish between carcinomas and the performance of convolutional neural networks and projection on latent structures is compared with discriminant analysis. They used a portable Raman setup to record the spectra of 615 patients with skin neoplasm's (70 melanomas, 122 basal cell carcinomas, 12 epithelioid cell carcinomas, and 413 benign tumors) in vivo, and then used those spectra to train classification models for use with convolutional neural networks and projection on latent structures methods. A 10-fold cross-validation was run on all of the models that were generated to ensure the categorization model was robust. Data was split into a training set (consisting of 80% of the spectrum dataset) and a test set (20% of the spectral dataset) to prevent model over fitting. Convolutional neural networks perform better than projection on latent structures across a range of classification tasks, as shown by the findings.

Classification of skin diseases using a Channel Attention-based Convolutional Network [2].

The purpose of this study is to use a Convolution Neural Network (CNN) to create a tool for the early diagnosis of skin disorders. EfficientNetV2 and the Efficient Channel Attention (ECA) block form the basis of the proposed model, Eff2Net. This study investigates the feasibility of replacing the quality Squeeze and Excitation (SE) block with the ECA block in the EfficientNetV2 architecture. In doing so, it became clear that the whole set of trainable characteristics was in high demand. When compared to other deep learning methods currently used for illness classification, the suggested CNN only had to learn only 16 M parameters. Acne, Keratosis (AK), Melanoma, and Psoriasis are the four types of diseases that were categorized in this way.

Attention-based deep convolutional neural network for automated skin lesion segmentation [3].
In order to improve the automated segmentation of dermoscopic images, a deep learning-based end-to-end system is developed. The encoder and decoder levels of the framework both make efficient use of Group Normalization (GN). Later, when the output loss function is implemented, Tversky Loss (TL) is included into Attention Gates (AG), which focuses on finer details inside the skip link. To effectively extract the feature maps produced by the encoding process, GN is used instead of Batch Normalization (BN). AGs are used to separate low-level irrelevant background areas from high-dimensional information in the input picture. To improve cooperation between recall and accuracy, Tversky Index (TI)-based TL is used. Atrous convolutions are used at the connecting bridge between the encoder route and the decoder path of the network to further increase feature propagation and promote feature reuse. To test the efficacy of the proposed model, we use the ISIC 2018 picture dataset.

Inflammatory dermatomes: a deep learning method to skin layer segmentation [4]
Segmentation and other forms of analysis are occasionally conducted manually by the doctor, with all the associated downsides (e.g., high costs in terms of both time and accuracy) that this entails. While HFUS has grown more popular in dermatology, it is only marginally supported by automated analytic techniques. To address the need for epidermis and SLEB layer segmentation and measurement, they created an automated segmentation approach. It begins with a preprocessing stage using fuzzy c-means clustering and ends with a U-shaped convolutional neural network. To strengthen the segmentation, the network uses batch normalization layers to scale and adapt the activation. The resulting segmentation results are checked and compared to the best available techniques for segmenting the skin layer. The computed Dice coefficients of 0.87 for the epidermis and 0.83 for the SLEB demonstrate the effectiveness of the suggested framework over other methods.

Using Convolutional and Artificial Neural Networks to Detect Skin Cancer [5]
The development of classifiers that can identify skin cancers from ceroscopy pictures is the primary emphasis of this article. Over 25,000 dermoscopic pictures with labels were included as part of the 2019 ISIC Challenge dataset used for training. Melanoma, melanocytic nevus, basal cell carcinoma, keratosis, benign keratosis, dermatofibroma, vascular lesion, epithelial cell carcinoma, and a variety of other benign skin lesions may all be distinguished from one another by categorizing dermoscopy pictures. Using Convolutional Neural Networks (CNNs), they built two types of classifiers for use on the Google Cloud Platform: a binary classifier and a multiclass classifier. They have employed picture data augmentation to prevent the classifiers from over fitting and increase accuracy despite a reduced quantity of training data. After 220 training iterations, the binary classifier was 73% accurate; after 200 training iterations, the multiclass classifier was 72% accurate. At last, the user is presented with a summary of the findings, including the illness kind, geographic range, and severity.

3. METHODOLOGY

First, we crop the photos to 28, 28 for more manageable learning, then we add the labels and names, and last we establish the plot settings. As a dependent feature, the image's pixels are recorded, while the label associated with the target serves as an independent feature. After the data has been separated into a train and test set and reshaped to account for imbalance (which can only be done if the data is 2 dimensional), the Random Oversample completes the task. After checking the new form against the training data, the data is reshaped to three dimensions and used to teach a convolutional neural network. Next, the Convolutional Neural Network model is established, and the CNN's first layer is drawn if the shape checks out. The maximum features discovered by the convolutional filter are chosen by max pooling. Next, Batch Normalization re-scales and re-centers the layer's inputs to make the Artificial Neural Network quicker and more stable. Dropout is employed to prevent over fitting in the fully connected Artificial Neural Network that is fed data from the Convolutional Neural Network. The foundation of an artificial neural network is established after this. The 7-neuron output layer is activated by a softmax function. In order to optimize, we employ the Adam optimizer with a learning rate of 0.001. Since we have several outputs, the model is first created with accuracy as the metric and loss as a Sparse categorical, and then the data is trained using a sample validation split of 0.2. Predictions are made using the model on the test data, and the resulting probabilities are then used to create classes. The model is then assessed for its efficacy. Approximately a thousand of these parameters cannot be trained on, out of a total of approximately half a million.

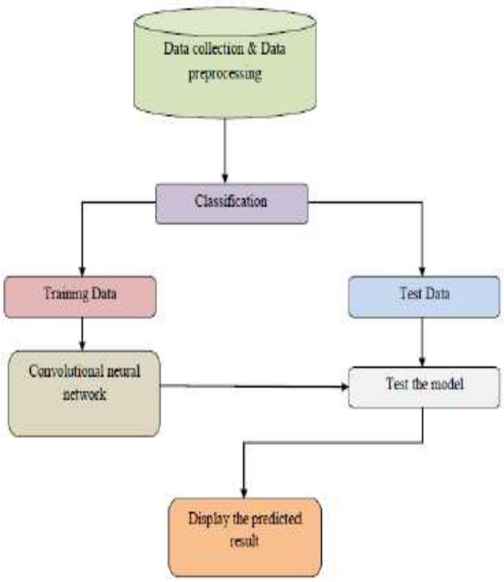

Fig -1: Data Flow diagram

The accompanying diagram shows how the data goes through several phases depending on what the prediction needs.

4. RESULTS

The approach was shown to have a disease prediction accuracy of between 74% and 75% for the aforementioned conditions. The model loss may be observed to drop suddenly at the outset before leveling out in the conclusion. As a result, there is a sharp improvement followed by a plateau at the conclusion. After extensive testing with various time settings, we settled on 50.

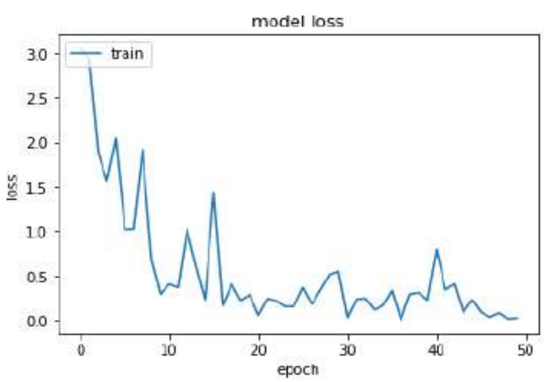

Chart -1: Model Loss Chart

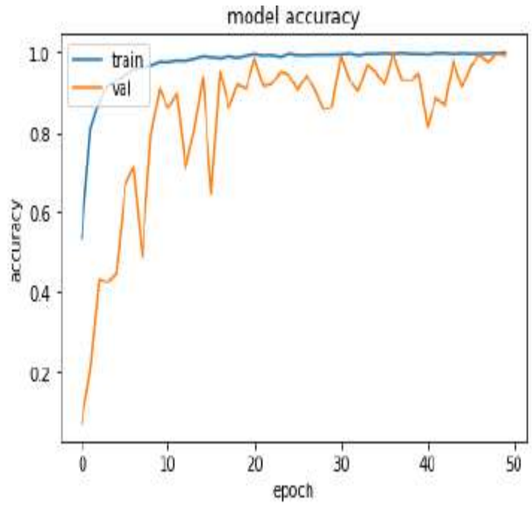

Chart -2: Model Accuracy Chart

Both plots show an improvement in model loss and system accuracy over time.

5. CONCLUSION

We find that the CNN model is correct to some degree, and that further development is possible with thorough inspection and a more trustworthy dataset. A mobile app based on the H5 file might provide instantaneous forecasts to users who submit images of the affected area of their skin.

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