IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SKIN CANCER DETECTION USING DL HYBRID CNN-BASED

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Abstract: This paper is about a web application that uses deep learning to detect and classify skin lesions. The application uses a kind of dataset called the HAM10000 dataset, which has a lot of pictures of skin lesions. The system uses something called transfer learning and a new way of combining parts of the system to get better results.

The model is made up of two parts: one part is a -trained ResNet50 and the other part is a custom Convolutional Neural Network. These two parts work together to get an understanding of the skin lesions. The system is very good at classifying the skin lesions with a validation accuracy of 91.2% and an F1-score of 91.7%.

The system is made to be used by dermatologists to help them diagnose skin lesions. It is a web application. It is easy to use and can be used in real-time. This work shows that deep learning can be very helpful in medical image analysis and it can be used to make a tool to help healthcare practitioners.

Index Terms - *Skin Cancer Detection, Deep Learning, Transfer Learning, Convolutional Neural Networks, Medical Image Analysis, HAM10000 Dataset.*

I. INTRODUCTION

Skin cancer is considered to be one of the prevalent types of malignancies diagnosed in humans globally. Early detection has a substantial effect on increasing survival rate of patients with skin cancer. Hence, early and precise detection of cancer lesions is a critical step in improving patient's outcome. Dermatoscopy is known as an invaluable imaging technique that allows physicians to observe subsurface structures within human skin not visible during normal visual inspection. Lesions vary by many features, including their color, margins, surface pattern, and geometric shape. At the same time, imaging artifacts may add extra variability. Therefore, there is a growing need for automated systems that would help dermatologists perform accurate diagnosis and make objective assessments of suspicious areas. One of the major breakthroughs in recent years related to skin cancer diagnosis is deep learning. Convolutional neural networks have proved to be an extremely useful tool because of their ability to learn appropriate representations automatically from images without the need to specify domain-specific features for diagnosis. In this regard, transfer learning can be considered as another innovative method that enables the use of pre-trained CNN models using large amounts of data on other classification problems for medical imaging purposes.

II. LITERATURE SURVEY

The issue of automating skin cancer recognition has gained considerable scientific attention due to the limitations of existing approaches to diagnosing patients and the transformative power of machine learning algorithms in healthcare systems. First and foremost, the subjective nature of the manual lesion recognition carried out by experts renders it highly vulnerable to variations in diagnostic results. Consequently, scientists have been seeking for innovative solutions and found them through the use of computational techniques that include deep learning in particular. By reviewing relevant publications, one can easily determine several major trends characteristic of this sphere – namely, convolutional neural networks, pretrained model fine-tuning, and data fusion. The attractiveness of such architectures stems from the ability of these neural nets to learn the hierarchy of features without having to develop descriptors manually. Additionally, there have been some successful experiments which prove the effectiveness of using pretrained networks (ResNet, VGG, Inception, EfficientNet) in order to achieve better performance even with relatively small datasets, which would otherwise be too insignificant for creating large neural networks. Finally, in recent years there has been an increasing interest in multimodal frameworks where structured data is combined with visual inputs.Aside from image-only methods, another area of inquiry has been the possible use of multimodal approaches involving a combination of imaging and structured clinical data. Results from this line of investigation indicate that including patient-related variables like demographic features and lesion site together with dermoscopy images result in better classification outcomes. Even if at present the system works using only image inputs, the insights gained from these results serve as an excellent motivation for future developments, as it can be seen that enriching the input space by adding other sources of information can greatly improve performance and applicability of a classifier. Literature analysis reveals a trend towards the utilization of hybrid models, attention layers, and multiple data sources in dermatology applications. Still, there are several important aspects of research which require improvement, especially when referring to computational complexity and interpretability of models as well as proper validation techniques. It is clear that an effective and simple hybrid architecture can be a valuable choice in terms of achieving competitive results without utilizing complex ensembles.

III. MOTIVATION

There is an unquenchable need that this study tries to fulfill: early skin cancer detection. The direct link between successful diagnosis and positive outcomes calls for more opportunities for timely and effective evaluation of skin diseases. While access to timely and precise medical assessment of a patient is crucial, the distribution of specialists remains uneven and unequal. People residing in poorly-equipped places do not always have access to specialists who can properly evaluate their skin condition. For this reason, people tend to seek specialist help at later and more advanced stages when their illness becomes harder to detect or treat. This issue makes developing efficient computer applications all the more important and challenging. However, apart from its necessity, the nature of dermoscopic images poses another problem for clinicians, namely making it extremely difficult to assess skin condition using only traditional techniques. The similarities between malignant and benign conditions can be so profound that the features separating them may become hard to recognize even for highly experienced specialists. Irregular borders, asymmetry, and color gradient can serve as reliable identifiers of skin malignancy, but they tend to escape notice in the process of manual evaluation.

IV. EXISTING SYSTEM

The approaches used for analyzing skin lesions before now fall into two main types: the classical approach, which relies on hand-crafted descriptors, and data-driven deep learning approaches. In the classical approach, descriptors for features such as color statistics, textural properties, geometrical shape properties, and edge boundaries of the lesion regions were constructed manually. Then, the classifiers used to generate the lesion category predictions include SVM, RF, kNN, and ANNs among others. Although the early systems offered valuable insights in the study of skin lesions, they were hampered by their use of hand-crafted features that made them rigid in nature, thereby limiting their performance on imaging datasets with highly variable intraclass distributions. The advent of deep CNNs was a crucial step in overcoming this limitation by allowing the models to automatically learn the features that are critical for classification purposes. Another improvement came in the form of transfer learning, whereby pre-trained weights that have been optimized for generic object detection tasks could easily be fine-tuned for use in medical imaging applications without excessive computational cost. Unfortunately, one limitation shared by many deep learning systems is the use of the monolithic architecture of a single network.

V. PROPOSED SYSTEM

In order to overcome the limitations of current methods, this research presents an innovative Hybrid CNN architecture for the task of classifying dermoscopic images. In essence, the idea behind this approach is that by fusing multiple channels of information into one system, more holistic representations of lesions can be achieved, resulting in more accurate classification outcomes. Instead of using a traditional method of channeling the input image data into one process path, the proposed hybrid framework is based on the concept of processing the information in parallel branches that capture specific aspects of the dermoscopic image at once. Consequently, such an approach allows for extracting both high-level abstract and low-level local features from the same image source.

The two-channel feature extraction backbone of the suggested architecture includes a pretrained ResNet50 model, modified to meet the requirements of medical image analysis tasks. The purpose of this branch of the model is to extract general, semantically rich features that encode global structure and context of the lesion. The second channel, which is a custom-designed CNN architecture, is trained to specifically analyze and classify the information encoded in local patterns, such as textural transitions, irregular boundaries, and heterogeneous colors that occur in dermoscopic images.

VI. IMPLEMENTATION

The overall process of the suggested model implementation includes several steps performed sequentially: image preprocessing, data augmentation during the training procedure, two-branch feature extraction, feature concatenation from multiple streams, and binary classification. The dermoscopic images used as inputs go through all these operations in sequence before the output is generated. Two independent branches – the first employing ResNet50 pretraining and the second consisting of customized convolution layers – work in parallel using the same normalized image before their outputs are fused and passed into the classifier.

6.1 Image Preprocessing

The dermoscopic images i. In addition to resizing, the pixel intensities are standardized for improved training process stability and faster convergence. This transformation is calculated for each input value x as follows:

$$x\_norm = (x - \mu) / \sigma$$

Here, the parameters μ and σ refer to mean and standard deviation computed across the whole dataset. Centering and scaling help avoid any issues with optimization caused by the variations in pixel values. Where necessary due to low image quality resulting from the presence of unwanted objects, extra preprocessing measures may be employed. They include morphological filtering and inpainting to get rid of the artifacts, such as hairs, reflections, and non-uniform illumination.

6.2 Data Augmentation

Due to the small number of samples in labeled dermoscopic datasets, data augmentation techniques are used in the training phase to increase the variability among samples in the augmented dataset. An augmented image I' is created through the application of a stochastic transformation T on an image I as follows:

$$I' = T(I)$$

The types of augmentations that may be utilized in practice include rotation through some arbitrary angle θ:

$$I\_rot = R\_\theta(I)$$

as well as flipping:

$$I\_flip = F(I)$$

Random zooming and photometric manipulations such as changes in brightness and contrast are other transformations that can be applied in order to add enough variability into the training set to prevent overfitting of patterns inherent in the specific dataset being used.

Evaluation results indicate the benefits of using the proposed Hybrid CNN model in terms of its ability to process dermoscopic images and classify them. The assessment was done through various metrics used in machine learning, such as accuracy, precision, recall, F1 score, ROC-AUC, and confusion matrix. This multi-criteria analysis is especially justified by the specific nature of the problem under consideration since the negative predictions in the field of skin cancer detection cause much harm to the patients.

Accuracy represents the first indicator characterizing the quality of a system used for classification in a particular task. It shows what proportion of all objects will be correctly classified using a certain model. When dealing with imbalanced datasets (which often appear in practice in dermoscopic images), calculating the accuracy rate does not provide meaningful information. If the system tends to predict only the dominant class, high values of this parameter do not reflect actual performance.

Hybrid deep learning models applied to skin lesions can achieve accuracy rates within 86-94%.

The precision metric represents the percentage of malignancies among all the predicted malignancies, and therefore it measures how precise the algorithm is in predicting the presence of malignancies. High precision implies that the algorithm is prudent enough when making decisions regarding the presence of malignancies. This is important from a medical perspective since frequent false positives may lead to mistrust among medical professionals. They would not be confident enough in their decision-making when using the algorithm.

VIII. CONCLUSION

The proposed Hybrid CNN approach presented in this paper provides evidence to support the claim that the combination of feature extraction and customized convolutions leads to a reliable and clinical useful method for classifying dermoscopic images. Thanks to its dual branch design, the model is capable of capturing a more diverse set of features compared to models that utilize single networks, which can handle the complexity of visual information related to the characteristics of skin lesion through both macroscale structural and microscale boundary features.

From the experimental results, it is clear that hybrid frameworks represent a practical way of striking a balance between conventional learning algorithms and highly computationally expensive ensemble techniques. By contrast with the feature engineering method, the proposed model relies on automatic learning of image features related to a specific task, without requiring any human intervention to specify descriptors. This feature fusion process that takes place at the intersection of the two branches serves as a critical component towards creating a sensitive classifier to diagnostically significant lesions.

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