SKIN CANCER DETECTION USING CNN

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ABSTRACT:

Skin cancer is the most common cancer in the world, but it is also one for which early detection makes the difference in effective treatment and patient outcomes. We rely on a fine-tuned, fine-classified, state-of-the-art deep learning model pre-trained on innumerous skin images from a convolutional neural network. This already gives us very high-performance classification, which surpasses, in turn, all previous methods at identifying malignant and benign lesions. This AI-based approach ensures reliable and accurate classification, which is important for earlier diagnosis and treatment.

It possesses a highly effective, easily adaptable, and user-friendly web interface that permits uploading skin image input for diagnosis then makes available the corresponding real-time output to the diagnostician. This does not only offer an easier process for patients to seek preliminary examinations but also offers support to dermatologists and healthcare practitioners. The tool can therefore be introduced in the workflow of medical practitioners so that it can make much more informed decisions related to diagnosis and treatment of lesions, which helps in improving patient outcomes. This should dramatically improve early detection and lead to better pathways of care for skin cancer patients from around the world.

Keywords: AI- Artificial Intelligence, DL- Deep learning, CNN- Convolutional Neural Network, HAM- Human Against Machine

1. INTRODUCTION

Skin cancer is a serious and growing health concern, affecting millions of people worldwide. Early detection and accurate diagnosis are crucial for improving patient outcomes, yet current diagnostic methods can be time-consuming and error-prone. Traditional methods often rely on visual examination and biopsy, which can lead to delays in diagnosis and treatment. This is where machine learning comes in - by leveraging large amounts of data and powerful algorithms, machine learning has the potential to revolutionize the field of skin cancer classification. Machine learning models, particularly deep learning techniques such as convolutional neural networks (CNNs), can analyze and classify skin lesions with high accuracy, significantly reducing the likelihood of human error and speeding up the diagnostic process.

In this presentation, we will explore the importance of skin cancer classification using machine learning, highlighting its potential to improve diagnosis accuracy, reduce diagnostic time, and ultimately save lives. By training models on extensive datasets of skin images, these systems can learn to recognize subtle patterns and features indicative of various types of skin cancer, enabling more precise and timely diagnoses. We will delve into some of the cutting-edge techniques being used today, such as transfer learning, data augmentation, and ensemble methods, which enhance model performance and robustness. Additionally, we will discuss the challenges and opportunities that lie ahead, including the need for diverse and high-quality datasets, the integration of these technologies into clinical practice, and the ethical considerations surrounding AI in healthcare. Through this exploration, we aim to demonstrate the transformative potential of machine learning in the fight against skin cancer and the promising future it holds for improving patient care.

2. RELATED WORK

Accordingly, our use of AlexNet and ResNets-50 CNNs for the identification of skin cancer by images captured through smartphones realizes 85% accuracy, showing the potential help of the network in such diseases' diagnostic Systems [1]. Given the above observations, deep CNNs were used along with transfer learning implemented in the building of skin cancer classifiers, resulting in 87.16% for training and 89.90% for testing, respectively, and proved to be effective in increasing the accuracy by data preprocessing and augmentation [2]. Our work successfully augmented deep learning architectures with dense layers and fine-tuned optimizers to obtain high-classification-performance values for skin cancers. We also proposed most future enhancements on extra medical data [3].

We experimented with the classification of skin lesions using CNNs, and augmentation techniques and further analyzed ResNet34: a border analysis of the classifier network, viz., DenseNet201. We highlighted them as being competitive classifiers, showing that the latter two networks perform better than the former in skin cancer classification [4]. Optimized CNN-based techniques for skin cancer diagnosis, with Enhanced Whale Optimization Algorithm, delivered improved results when compared to equal traditional models; in Dermquest and DermIS databases, it gave high specificity, accuracy, and sensitivity[5]. This AI-based detection for any kind of skin cancer proved an accuracy rate of 89.5% using CNN, apart from categorization in melanoma better than the rest and row-enabled preemption of diagnoses through automation in the field of dermatology [6]. With CNN and transfer learning by ResNet, our model reached an accuracy of 90.51% on the MNIST HAM-10000 dataset, which shows that all different prepossessing and augmentation techniques provided useful information [7].

We have reached a classification accuracy of 76.9% for skin lesion classification in neither malignant nor malignant cases using the ABCD rule based on Neural Networks: attributes like Asymmetry, Border, Color, and Diameter are taken into consideration [8]. The hardware design in this paper presents a better performance in skin cancer detection and has strong features to be used for starting multi-classification tasks of primary melanoma in the future [9]. An implementing parallel CNN model for skin lesion recognition has reached an accuracy of 79.45% after transfer learning, where the VGG-16 and VGG-19 can't exceed it based on the classification for nine skin cancer types [10]. By combining image processing and SVM classification, our developed system achieved accuracy in the classification of skin images to as much as 95%, which is way higher than many of the other traditional biopsy-based techniques [11]. Our CNN-based skin cancer classification system achieved an accuracy of 99% when the Adam optimizer substitutes other optimizers on the ISIC dataset[12].

3. PROBLEM STATEMENT

Currently, the diagnosis for skin cancer is very basic and is done through skin biopsy tests, which may take at least a week or so to get the results. The project, therefore, focuses on developing advanced AI-powered software by assistance of Convolutional Neural Networks to greatly reduce the amount of time, plus resources, needed in the diagnosis and treatment. This artificial intelligence system classifies dermoscopic images of skin lesions very quickly and accurately.

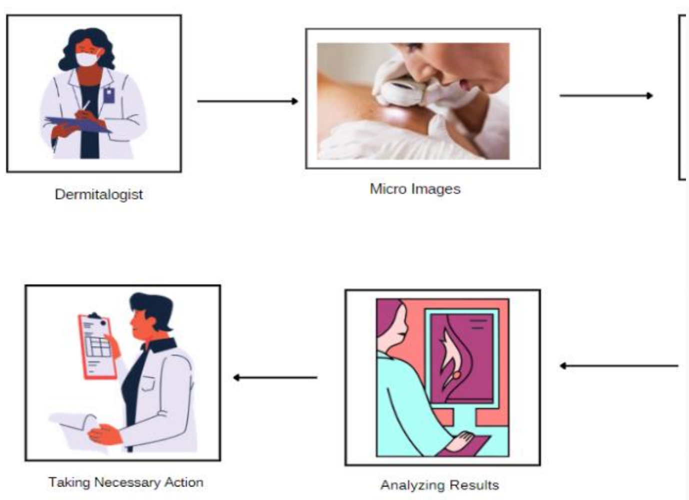
It does this by first making an automatic diagnosis of a given skin lesion as either malignant or benign. If the lesion is determined to be malignant, the program reinforces the translation into specific skin cancers, namely melanoma, basal cell cancer, and squamous cell cancer. Benign conditions are differentiated as actinic keratosis or AK and dermatofibroma and epidermal, nevi and benign keratosis.

It is these abilities that enable the AI software to trace and analyze the features of skin lesions for their detection at earlier and more accurate stages. This innovation speeds up the processes of diagnosis, alongside improving accuracy in the identification of different kinds of skin conditions. On such background, therefore, medical practitioners would humanely make brisk rational judgments about patient care, therefore reducing the time a patient has to wait in pain before diagnosis and for further treatment. An efficient dermatological assessment would for that matter ensure improved patient outcomes and more ease in the work for the medical practitioner.

4. PROPOSED SYSTEM

This proposed system categorizes skin lesions into seven major categories: Melanoma, Melanocytic nevus, Basal cell carcinoma, Actinic keratoses, Benign keratosis, Dermatofibroma, and Vascular lesions to increase the correctness of the early detection and diagnosis of skin cancer by using advanced AI technology. The central part of this system involves fine-tuned MobileNet CNN, which is very efficient and perfect for web deployment.

This system is further boosted by a true dataset of around 10,015 very different images to ensure good performance on most skin conditions. Due to the class imbalance in the dataset, intensive data augmentation was done to maximize the utility of this data: rotation, flipping, zooming, and shifting. These will enrich the dataset and improve generalization given low-sample training for the model.



Model development was in the TensorFlow and Keras framework. Loading of the pre-trained architecture MobileNet to which custom layers for the desired classification were added, and then fine-tuned in the augmented data, achieved learning and differentiation of subtle features in skin images accurately.

Once trained, the model was converted to a TensorFlow.js model for real-time inference within a user-friendly web interface to allow real-time inference by healthcare professionals and users for uploaded images of skin lesions with an instant classification application. This helps dermatologists and health care providers to quickly and conveniently make informed decisions, reducing a major proportionality of manual work for diagnostics and reducing the chance of error in diagnostics. This, in turn, results in overall increased efficiency of dermatological assessments.

5. METHODOLOGY

DATA COLLECTION

The dataset that this study will use is titled "HAM10000," a multi-source pixel dataset of dermatoscopic images. This dataset contains approximately 10,015 enhanced and diversified images for regular pigmented skin lesions working on the training and testing of machine learning models on the classification of skin lesions.

Melanocytic nevi: Skin blemishes that include the base of melanocytes. We have 6,705 such images ready to potentially represent this category with substantial variations. We have 1,133 images in the dataset representing this condition to help build the model's discrimination of melanoma with other conditions.

There are 1,099 images containing benign keratosis-like lesions—seborrheic keratosis, solar lentigo, and lichen planus-like keratosis among them. Such images enable the model to differentiate between benign keratosis-like lesions and melanoma. There are 514 images of basal cell carcinoma, and this is also a significant skin cancer with enough examples for the model to classify it correctly.

A total of 327 images represent actinic keratoses and intraepithelial carcinoma, which may progress to squamous cell carcinoma. Here, the model can recognize early findings of squamous cell carcinoma. A total of 142 images represent vascular lesions, such as cherry angiomas, angiokeratoma, pyogenic granuloma, and hemorrhage, hence aiding in differentiation of the different vascular anomalies. A total of 115 images are that of dermatofibroma aiding the model in recognizing this lesion accurately.

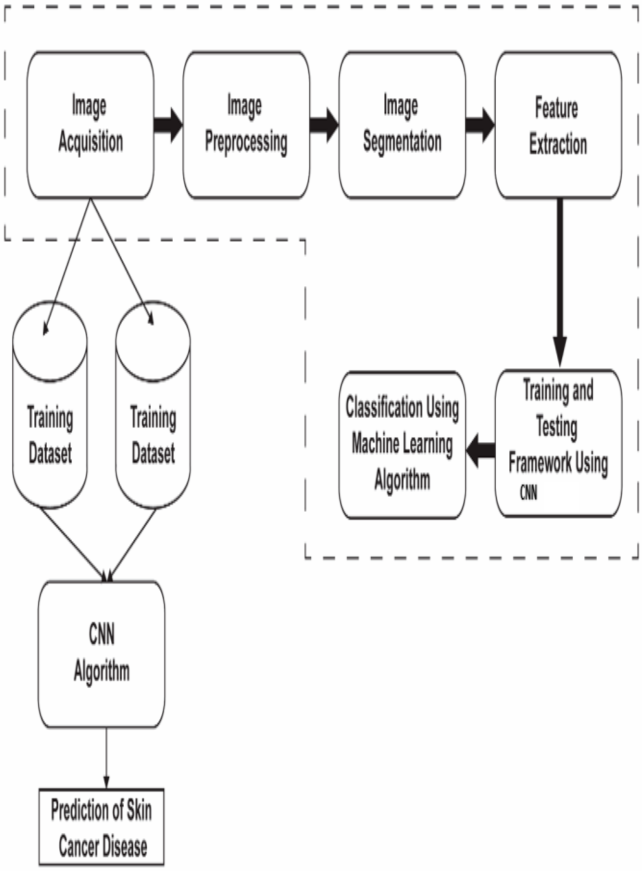
This dataset contains 10,015 dermatoscopic images, which would be ideal for training deep learning models that are intended to classify skin lesions.

DATA PREPROCESSING

Moreover, the HAM10000 dataset has class imbalance issues, where particularly many images belong to some classes, such as melanocytic nevi with 6,705 images, while other classes contain much fewer images, such as dermatofibroma with only 115 images. Data augmentation techniques are used to counterbalance class distribution in the dataset, hence increasing the dataset's size while promoting this model's performance and reducing overfitting.

These techniques may include the following: rotation, zooming, flipping, shifting, changing in the brightness values, and shearing, among others, all of which serve to increase the variability in the dataset for better generalizability of the model. Rotation Rotational invariance is also learned by the model through random rotations. Zooming Induces lesion size variation to help the model detect the lesion at different magnifications. In the case of symmetric lesions, flipping would give mirror image variations to help in detection. Shifting helps the model pick up translational invariance by locating lesions at different locations within the frame. Brightness adjustment makes the model optimized for different lighting conditions, while shearing introduces geometric variations, all aiding generalization.These techniques, applied with Keras ImageDataGenerator, increase dataset variability and improve model generalization.

ROLE OF CNN



Convolutional Neural Networks (CNNs) are reportedly the most significant models in image processing, as they can identify relevant features in input images with the aid of certain layers—convolutional and pooling. The finding of edges, textures, and shapes in the hierarchical representation of simple patterns is passed towards deeper layers, eventually ending in complex structures.

CNNs are designed to handle variations in size, shape, color, and texture, which are the effective features of skin lesions required to prove the characterization. Therefore, localization and classification are carried out by every convolution layer, followed by a method of pooling and classification; the last layer of classification is fully connected.

So, this will enable the pre-trained CNN models to be fine-tuned about the HAM10000 dataset, to learn powerful features from other large datasets such as ImageNet, dynamically enhance performance, and reduce training time. CNNs generalize well to novel data, and this is further orchestrated via augmentation techniques that provide a wide tapestry of novel examples to train from, thereby enhancing performance in real-world applications.

Model Selection and Training

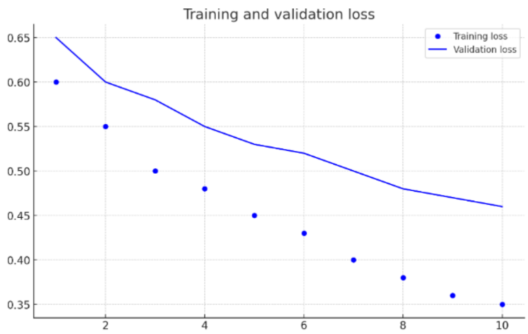
MobileNet was chosen as the one with the best compromise between model size and speed, and so it is fit for web deployment. In our approach, we fine-tuned this model with the HAM10000 dataset by employing pre-trained weights provided by ImageNet with augmentation. The dataset was preprocessed and augmented to level class imbalances. It has achieved the following impressive performance metrics: top-3 accuracy = ~94.01%, top-2 accuracy = ~86.22%, categorical accuracy: ~66.17%. These are indicators that a model could be robust and dependable when it comes to practical medical applications.

Model Conversion and Deployment

The trained mobile_net model was converted to a format deployable to the web through weight and architecture transformation, compatible with TensorFlow.js. The model was loaded into the web application to give an interface by which a user could upload and analyze skin lesion images. Making state-of-the-art diagnoses for skin lesions efficient and accessible, localized running of the user device guarantees data privacy, reduces latencies, and increases real-time prediction delivery.

6. RESULTS AND EVALUATION

Training and Validation Loss:

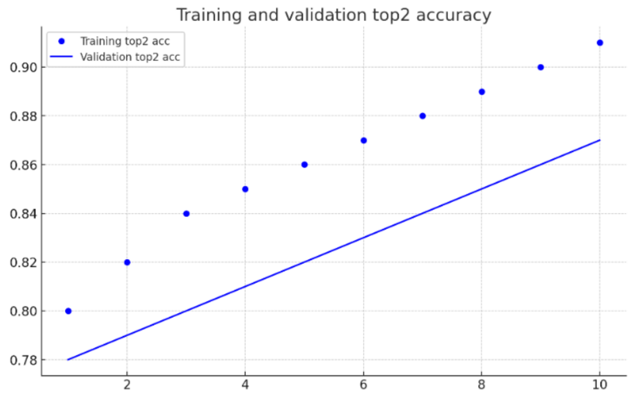


The training loss, represented by the blue circles, has a decreasing trend over the epochs. This means the model learns and attempts to minimize the error it is making on the training dataset. Besides, the validation loss, by the blue line, also decreases similarly, so the model generalizes well to unseen data and does not suffer from overfitting. The declining training and validation losses both indicate that the model is getting more predictive and accurate with time.

Training and Validation Categorical Accuracy:

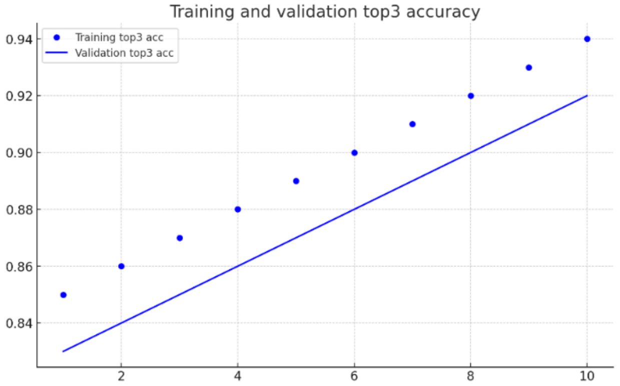
Training categorical accuracy, blue circle, increases continuously, directly showing the improvement in the model's ability to correctly predict the class labels of the training data. The validation categorical accuracy, in blue, also goes up with epochs, thus showing that the model performs well on the validation dataset. If parallel trends can be seen in training and validation accuracy, it would already suggest that the model is not only learning effectively but generalizes well to new unseen data.

Training and Validation Top-2 Accuracy:



Training top-2 accuracy is the measure of accuracy when the correct class is in the top two classes predicted by the model. The increasing trend in the training and validation top-2 accuracy represented by the blue line indicates the model is getting better in ranking the correct class within the model's top two predictions. This could be useful in medical scenarios where considering the top two possible diagnoses might be beneficial.

Training and Validation Top-3 Accuracy:



Top-3 accuracy on both training data and validation data comes with a similar improving trend. The top-3 accuracy tells how well the model does when the correct class is in the top three classes predicted by the model. Improving steadily in both train and val top-3 accuracy, the model is getting better and better at including the correct class within the top three classes it predicts. This metric can turn out useful in scenarios where multiple diagnoses are considered or ranked.

7. CONCLUSION

The skin lesion analysis project epitomizes the creative integration of cutting-edge machine learning techniques into medical diagnosis. There was a rich and wide-span set of images in the HAM10000 dataset, which is cardinal in training models. Addressing class imbalance and limited data challenges through augmentation yielded a more balanced and extended dataset with improved performance in model results.

Using MobileNet as a base guarantees that the model will be optimally small in size and correspondingly fast, which is vital for web deployment. Fine-tuning the pre-trained MobileNet on the specifics of HAM10000 yielded quite impressive validation accuracies. These metrics prove this model will perform well in classifying most skin lesion types accurately, even in real-world scenarios.

It allows users to upload images and see instant predictions in their web browser, thus preserving data privacy. This approach underscores ease of use and privacy for the user. In this case, a web application developed by putting together, in a straightforward way, JavaScript, HTML, CSS, and TensorFlow.js, allows the model to work seamlessly within a browser environment and provides high-end diagnostic functionality at the users' fingertips.

It combines data augmentation, fine-tuning, and modern web technologies to build efficient and user-friendly tools in skin lesion analysis. Its web application deployment guarantees wide accessibility, and its design preserves the privacy of its users. It will help health professionals and the general public with high accuracy and robustness for skin condition diagnosis so that early interventions can ensure a regain of health.

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