Lesion Melanoma Classification Using ResNet50v2

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ABSTRACT

A severe form of skin cancer called melanoma claims thousands of lives every year. It has become much more common in recent decades, and early detection is critical for lowering mortality rates and increasing chances of recovery. A dermoscopy procedure is typically used to diagnose skin lesions that can lead to melanoma. These dermoscopic images are then examined to determine the presence of skin cancer by inspecting the colour, shape, size, and changes in these skin lesions. Several models, such as CNN, have been used in the past to detect and classify melanoma. In our model, we aim to increase the accuracy of these models to make detection and classification easy and precise. We have used skin lesion images from an ISIC dataset for our model. Using Keras applications like ResNet50V2 functions, we have achieved an overall improved accuracy.

Keywords

Lesion Melanoma classification; Dermoscopic images; Resnet50v2 model; Machine learning; Melanoma detection

1. INTRODUCTION

The World Health Organisation (WHO) has identified skin cancer as one of the worst malignancies that have recently spread significantly over the globe. It is crucial to find and remove the skin lesion as soon as possible since the timely detection of a skin lesion is crucial to its successful treatment. Otherwise, it will grow and spread, go deeper into organs, and cause additional complications.

Melanoma develops when melanocytes, which are skin cells, mutate and grow uncontrollably. The DNA of skin cells is damaged by ultraviolet or UV light, which is the main cause of skin cancer. UV light is primarily emitted by the sun. Melanoma, unlike other types of skin cancer, can appear on parts of the body that are not normally in direct contact with sunlight, such as the groin or armpits. Although the exact reason for melanoma is unknown, several risk factors may raise the likelihood of the disease developing. The main risk component for melanoma is prolonged contact with ultraviolet (UV) light, which includes sunlight, tanning beds and sun lamps, with the risk increasing with the level of exposure. Melanoma risk rises with early sun exposure, especially in people who were sunburned frequently as children.

Melanoma is more likely in people who have a lot of moles on their bodies, especially if they are larger than 5mm or have an odd shape. As a result, it is critical to monitor the moles and keep them out of direct sunlight. A dermatologist or other doctor with expertise in skin conditions can make the diagnosis of skin cancer. Regular skin exams can also be done by dermatologists. Many dermatologists use dermoscopy, also referred to as dermatoscopy, epiluminescence microscopy (ELM), or surface microscopy, to examine spots more thoroughly on the skin. The dermatologist could also take a picture of the spot to examine.

Most lesions are easily detectable with a visual aid, but it can be difficult for the average person to determine whether a mark is a lesion or a harmless discolouration of the skin, such as a birthmark. Melanoma is a particular kind of skin cancer that is highly lethal. Due to their high similarity, melanoma skin lesions are frequently misdiagnosed. Melanoma skin lesions very often resemble other lesions, such as nevus and keratoses, making diagnosis more difficult. Melanoma is also considered one of the most serious types of cancer, so it must be detected early before it becomes malignant or metastasizes, i.e. grows uncontrollably and affects other body parts.

CNN, or convolutional neural networks, are now being used to classify melanoma lesions with a relatively high success rate. However, CNN struggles to be efficient when the image is noisy. For example, in lesion images, there can be hair, coloured patches, blood vessels etc present around the lesion with makes image extraction much more difficult for a CNN model, thus making it less accurate. Through our proposed model, we aim to improve the accuracy of the detection and classification of melanoma.

The dataset utilised in this study is the "Skin Cancer MNIST: HAM10000" dataset, which contains more than 10,000

dermatoscopic images of skin lesions divided into seven benign and malignant categories. It contains information including the age of the patient, sex, and area where the lesion is located and is used to train machine-learning models for skin lesion diagnosis and categorization. Figure 1 depicts seven different types of lesions that are present in the dataset used.

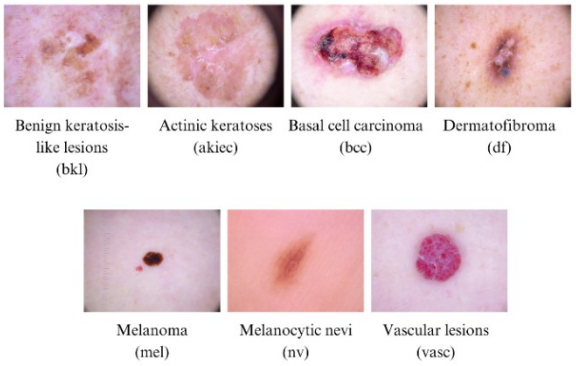

Figure 1. A dataset consisting of images of the seven classes of skin lesions

2. RELATED WORKS

In the process of preparing our model, we referred to several research papers and resources, intending to identify and overcome the limitations posed by previous models.

A methodology for automated initial melanoma detection utilising a sequential dermoscopic image model was presented to achieve greater diagnostic performance than clinicians (63.69% vs. 54.33%) and deliver melanoma diagnosis sooner [1]. It was ineffective at classifying lesions as low-risk or high-risk.

To investigate inter-categorical interactions, another model, a graph-based relational module (GRM), was presented [2]. GRM depicts diagnosis with two-star graphs, one for each dermoscopic or clinical imaging modality. This differs from previous multimodal techniques, which do not explicitly include label dependencies. Nevertheless, if the model is to be implemented, threshold values for the anticipated probability must be selected. The risks associated with false positive and false negative classifications must be weighed.

Zhang B. et al. proposed a new method based on deep learning for automatically spotting changes over a short period in melanoma screening [3]. Tensorial Regression Process, a unique Siamese structure, was presented to obtain global characteristics of lesion pictures concerning deep convolutional characteristics. The drawback discovered was that if the lesion does not change in a short period, the screening will fail.

The modified versions of the InceptionV3 model as well as the VGG16 model were proposed which classify skin cancer with a better accuracy value [4]. This model uses CNN for image classification. The used dataset in this work contains three classes: melanoma, nevus, and seborrheic keratosis. They are also classified into benign and malignant classes. The two models are compared with other models like KNN and show an increase in accuracy. To increase classification performance in this model, data imbalance may be decreased, although careful adjustment is needed. The two given models as well as deep learning models can be combined to improve performance.

The model proposed by M. D. Alahmadi deals with the segmentation of the skin lesion area [5]. To simulate the hierarchical representation, the author presented a Multi-Scale Attention U-Net (MSAU-Net), which enhanced the standard U-net by adding an attention mechanism at the network's bottleneck. This technique learns the intricate structure of the lesion and precisely segments the aberrant regions, producing a smooth segmentation result on the boundary area and separating the lesion area from the overlapping backdrop. The model's performance may be further improved by correctly modelling the skin lesion's weak annotation during training.

Fraiwan M and Faouri E. proposed to use of deep transfer learning images of skin lesions to classify them into seven groups, by building a system (using 13 DTL models) which takes dermoscopic images as input without explicit feature extraction or preprocessing [6]. Thirteen deep transfer learning models were used in its development. Using dermoscopic pictures of the skin lesions as input, they created an AI-based testing tool for skin cancer (melanoma and non-melanoma) that can assist with clinical screening tests, minimise mistakes, and enhance early identification. This collection may be enhanced, though, by collecting dermoscopy photos of uncommon skin lesion types to make them accessible to the scholarly community.

A model consisting of a smartphone application, which consists of a real-time non-invasive skin lesion analysis system to help to prevent melanoma and for helping in detecting it early was proposed by VS. Sabeera and P. Vamsi Krishna [7]. The system is divided into two parts: a real-time warning to prevent sunburn and an automatic visual analysis utilising a database of 200 dermoscopy photos with image capture, hair recognition and exclusion, lesion segmentation, feature extraction, and classification. To categorise the images into benign, atypical, and melanoma, it suggests an automated segmentation method and unique characteristics. We found that this model can be improved by an algorithm like CNN along with morphological segmentation to increase the performance and accuracy of image processing.

In another model, CNN is used for binary classification of melanoma, which examines current approaches for using deep learning to detect melanoma and assesses present developments in research, difficulties, and possibilities of diagnosing melanoma [9]. Datasets like ISIC Archive, PH2 Dataset, etc are used. This paper provided a thorough analysis of these solutions based on similarities and differences. The limitation discovered here is that a larger dataset must be used to fine-tune hyper-parameters and lower the likelihood of overfitting. To reach high accuracy, CNN must also learn to collect data from people with a dark complexion, and age, gender, and race must be taken into account.

The region of interest in a dermatoscopic image is automatically cropped with the Mask and Region-based Convolutional Neural Network technique in the first step of the procedure described in Paper [9]. The second step, which makes use of the ResNet152 structure, labels lesions as "benign" or "malignant," based on their makeup. Training, validation, and testing were carried out using the database. To identify the existence of melanoma, an automatic classification approach for a cutaneous lesion in digital dermatoscopic images was given. Stage 1 entails utilising Mask R_CNN to trim a bounding box around just the skin lesion in the input picture, and Stage 2 requires classifying the bounding box that was cut out using

ResNet152. We found that classification performance can be improved with careful fine-tuning; for instance, creating perfectly balanced training data does not always provide a better model.

A summary of the automated melanoma detection in dermoscopy images is given in the paper [10]. First, lesion segmentation is done and then the classification is done where melanoma existence is predicted using algorithms based on machine learning. PH2 and EDRA image databases are used. The lesion border may be used to compute lesion characteristics such as estimated diameter, irregularity, symmetry and eccentricity. Any one of the available classifiers is used for implementation. However, dermoscopy pictures contain a variety of aberrations and artefacts, making it essential to use the right procedures and techniques to correct these anomalies and arrive at the right diagnosis.

Taking into consideration the limitations found in the above papers and models, we have made an effort to create a model overcoming those limitations and with improved accuracy and features.

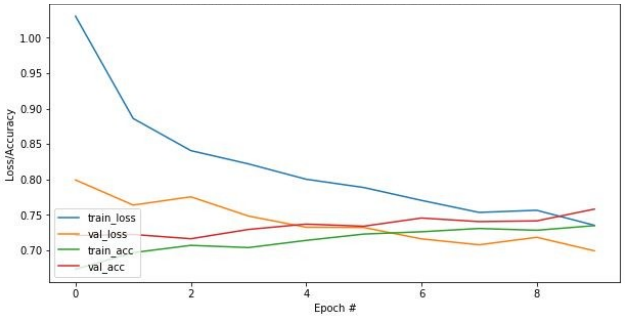

Figure 3. Training Loss and Accuracy on dataset - ResNet50v2

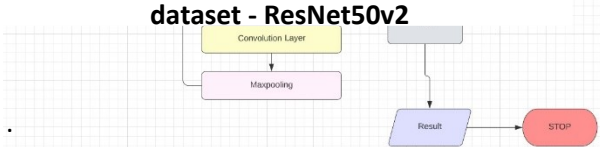

Figure 2. Flowchart of the proposed model

3. PROPOSED MODEL

The strategy we utilised in our study to categorise lesion melanoma using deep learning techniques is described in this part. The main objective of this work was to create a lesion melanoma classifier using a ResNet50v2 deep-learning model that was reliable and accurate.

Figure 2 depicts a flowchart for a computer vision algorithm that takes an image and then processes it with convolution and max-pooling layers. The modified picture is placed on the original image and submitted to a database-based neural network logic. Given the data provided by the image and the database, the neural network provides a result. The system is intended to conduct image analysis and classification tasks, and it may be utilised in a variety of applications, including medical diagnosis, recognition of objects, and monitoring.

- **Data collection and pre-processing:** The study utilised 10,015 images of a skin cancer dataset from Kaggle. Images were categorised, null values were handled, renamed, resized, and data was moved as part of the pre-processing stages.
- **Data Split:** Data were split into two groups: training sets, which contained 80% of the data, and validation sets, which had 20% of the data. Additionally, this data will be normalised to get rid of unnecessary information, cut down on data modification errors, and make querying easier.
- **Data Augmentation:** Data augmentation was carried out on the training data to expand the size of the training set and decrease overfitting. Rescaling, shearing, zooming, horizontal flipping, width shifting, height shifting, and fill mode closest were among the augmentation techniques utilised.
- **Model Selection:** The ResNet50v2 deep learning model was chosen for this study because of its capacity for handling huge picture datasets and its capacity for extracting features from images.
- **Model Architecture:** The model's head was constructed on top of the ResNet50v2 model, which was used as a base. The head model consisted of an average pooling layer, a flattening layer, a 64-neuron dense layer with a ReLU activation function, a 0.5-rate dropout layer, and a 7-neuron dense layer with a softmax activation function.
- **Model Training:** The categorical cross-entropy loss function and the Adam optimizer were used to train the model. The decay was set to 1e-4/200 and the learning rate at 1e-4.
- **Evaluation:** The validation data were used to assess the model's performance. The main performance metric was calculated based on the model's accuracy.
- Now, the main task will be to test different models to verify their accuracy. Keras API provides several deep learning models like Xception, ResNet50V2, InceptionV3, MobileNetV2, etc. The standard image classification model such as CNN and ANN can be used to compare the accuracy. When tested CNN with ANN on the same dataset, a large difference in accuracy was noticed.
- When several Keras API models were evaluated, MobileNetV2 achieved an accuracy of 50.21% and Xception achieved an accuracy of 62.32%. On a smaller database sample, ResNet50V2 fared the best, averaging 76.55% accuracy.

4. RESULT ANALYSIS

In this study, deep learning methods were used to handle the Lesion Melanoma Classification challenges. A dataset of skin lesion photos was used to train and verify a ResNet50v2 model. The data was pre-processed by sampling the data and were then scaled to have pixel values between 0 and 1, and the data were split into 80% training and 20% validation sets.

Data generators were created using the ImageDataGenerator class from the Keras library. The training generator applied data augmentation techniques such as rescaling, shearing, zooming, flipping, and shifting to expand the training set's size and avoid overfitting. The validation generator only rescaled the data.

The ResNet50v2 model was loaded from the Keras library and its last few layers were retrained using a new head model. The head model consisted of an average pooling layer, a dense layer with 64 neurons, a dropout layer, and a final dense layer with 7 neurons for the 7 classes in the dataset. The

categorical cross-entropy loss function and the Adam optimizer were used to compile the model.

The loss and accuracy of the ResNet50v2 model can be seen against the number of epochs in Figure 3. The blue and yellow curves reflect the training and validation losses, whereas the green and red curves show the training and validation accuracy, respectively. The graph indicates that increasing the number of epochs reduces training and validation losses while increasing training and validation accuracy. Furthermore, the slope of the loss curves eventually approaches zero, whereas the slope of the accuracy curves approaches infinity. It is worth noting that the change in the slope of the loss curves is not proportionate to the increase in training and validation accuracy.

The model was trained for 10 epochs, and its accuracy was monitored during the training process. The model was able to accurately categorise the skin lesion photos into one of the seven classes, as evidenced by the final validation accuracy attained of 80.14%.

In comparison, the graph in Figure 4 depicts the VGG16 model's performance over numerous epochs. The graph shows that as epochs increased, training and validation losses reduced, while training and validation accuracy stayed flat with small increases.

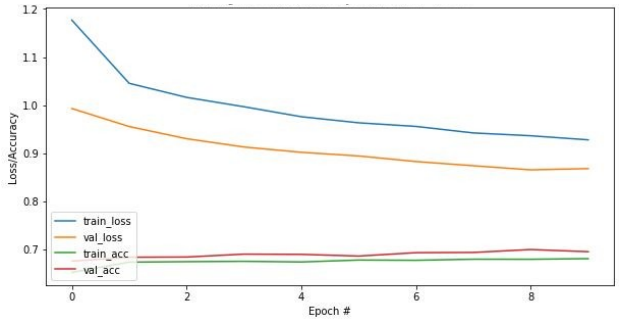

Figure 4. Training Loss and Accuracy on dataset - VGG16

5. CONCLUSION:

In conclusion, this work demonstrated the use of deep learning techniques to categorise lesion melanoma. We implemented the model with the highest accuracy after comparing different machine learning models. The ResNet50v2 model was able to achieve high accuracy on the skin lesion image dataset, making it a promising tool for dermatologists to identify skin cancers.

However, it should be noted that this study only used a single dataset, and further experimentation is required to assess the model's efficacy on additional data sets and in real-world situations. The model's limitations and future directions for improvement should also be investigated. In conclusion, this study emphasises the significance of ongoing research in the area of computer-aided diagnosis, particularly in the field of dermatology, where prompt and precise diagnoses are essential for successful treatment.

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