Lesion Melanoma Classification Using ResNet50v2

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ABSTRACT

Melanoma is a deadly type of skin cancer that kills thousands of people each 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 will be using 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 Organization (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 majority of skin cancers are caused by ultraviolet or UV light damaging the DNA in skin cells. UV light is primarily emitted by the sun. Melanoma, unlike other types of skin cancer, can appear on areas of the body that are not normally exposed to sunlight, such as the groin or armpits. While the exact cause of melanoma is unknown, several risk factors may raise the likelihood of the disease developing. The primary risk factor for melanoma is exposure to ultraviolet (UV) light, which includes sunlight and tanning beds, with the risk increasing with the amount 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 large (more than 5mm) or unusually shaped. As a result, it is critical to monitor your moles and avoid exposing them to direct sunlight. Skin cancer can be diagnosed by a dermatologist or a doctor who specialises in skin problems. Dermatologists can also perform routine skin exams. Dermoscopy, also known as dermatoscopy, epiluminescence microscopy [ELM], or surface microscopy, is a technique used by many dermatologists to examine spots on the skin more closely. A photograph of the spot may also be taken by the dermatologist for examination.

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.

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 novel deep learning-based method for automatically detecting short-term changes in melanoma screening [3]. Tensorial Regression Process, a unique Siamese structure, was presented to extract global characteristics of lesion pictures in addition to 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]. In order 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 possible categories, by building a system (using 13 DTL models) that accepts dermoscopic images as input without explicit feature extraction or preprocessing [6]. It was developed using 13 deep transfer learning models. They developed an artificial intelligence-based screening system for skin cancer (melanoma and non-melanoma) using dermoscopic images of the skin lesions as input, which can help with clinical screening tests, reduce errors, and improve early diagnosis. This dataset can be improved, however, by gathering specific dermoscopy images of under-represented skin lesion types and making them publicly available in the research domain.

A model consisting of a smartphone application, which consists of a portable real-time non-invasive skin lesion analysis system to assist in melanoma prevention and early detection was proposed by VS. Sabeera and P. Vamsi Krishna [7]. The first part of the system is a real-time warning to help users avoid sunburn, and the second part is an automated visual analysis using a database of 200 dermoscopy images that include image capture, hair

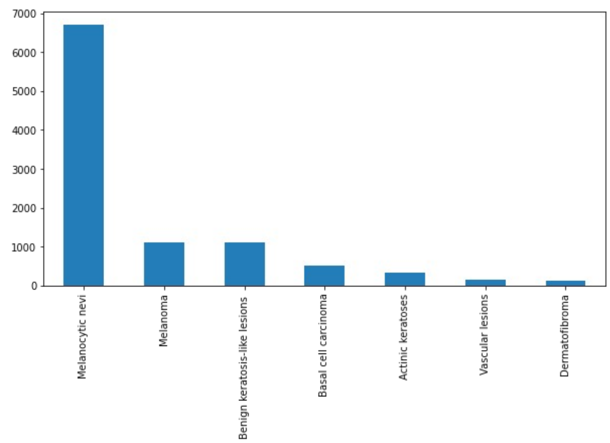

Figure 1. Dataset consisting of images of the seven classes of skin lesions

re cognition and exclusion, lesion segmentation, feature extraction, and classification. It proposes an automated segmentation algorithm and novel features to classify the images into benign, atypical and melanoma. 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 solutions for the diagnosis of melanoma detection using deep learning and analyses the recent research trends, difficulties, and prospects for melanoma diagnosis [9]. Datasets like ISIC Archive, PH2 Dataset, etc are used. This paper provided a systematic review of these solutions based on similarities and differences. The limitation discov8red here is that a larger dataset must be used by performing fine-tuning to hyper-parameters which can reduce the chances of overfitting. Moreover, CNN must learn to fetch data from dark-skinned people to achieve high accuracy and age, gender, and race must be considered to achieve better results.

In the initial stage of the method described in Paper [9], a dermatoscopic image's region of interest is automatically cropped using the Mask and Region-based Convolutional Neural Network technology. The second stage, which uses the ResNet152 structure, categorises lesions as "benign" or "malignant," depending on their nature. Using the database, training, validation, and testing were conducted. Thus, an automated classification method for a cutaneous lesion in digital dermatoscopic images was proposed, to detect the presence of melanoma. Stage 1 involves cropping a bounding box around only the skin lesion in the input image, using Mask R_CNN, and Stage 2 involves the Classification of the cropped bounding box using ResNet152. We found that classification performance can be improved with careful fine-tuning; for example, making training data perfectly balanced does not always result in a better model.

In the paper [10], an overview of the computerized detection of melanoma in dermoscopy images is provided. 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've made an effort to create a model overcoming those limitations and with improved accuracy and features.

3. PROPOSED MODEL

The strategy we utilised in our study to categorise lesion melanoma using deep learning techniques is described in this part. The major goal of this study was to develop a lesion melanoma classifier that was accurate and trustworthy utilising a ResNet50v2 deep learning model.

- **Data collection and pre-processing:** The Kaggle repository was used to access the dataset for this investigation. The collection includes 10015 pictures of various skin conditions, including both benign and cancerous conditions. The data needs to be preprocessed before training it. Since a large number of images are provided, we need to categorise the images according to the features and patient details. The data needs to be cleaned by checking any null values in the dataset and then replacing the null values with the mean. The photos were renamed, the images were resized, and the data was moved, as part of the pre-processing.
- **Data Split:** The data were divided into training and validation sets, with training sets using 80% of the data and validation sets using 20%. This data will also be normalised to eliminate redundant information, reduce data modification errors, and simplify the query process.
- **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 model was trained using the categorical cross-entropy loss function and the Adam optimizer. The learning rate was set to 1e-4 and the decay to 1e-4/200.
- **Evaluation:** The effectiveness of the model was evaluated using the validation data. The primary performance metric was calculated based on the model's accuracy.

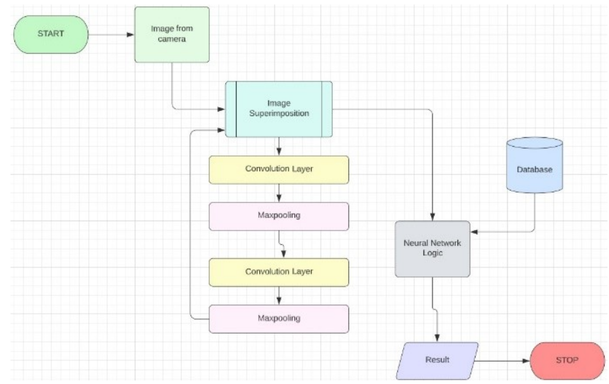

Figure 2. Flowchart of the proposed model

- 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.
- A CCN or Convolutional Neural Network is a special class of neural networks that are built with the ability to extract unique features from image data, whereas ANNs or Artificial Neural Networks are nonlinear statistical models that use a complicated interaction between inputs and outputs to discover a new pattern. When tested CNN with ANN on the same dataset, a large difference in accuracy was noticed.
- Similarly, different models from Keras API were tested. The MobileNetV2 gave an accuracy of 50.21% accuracy whereas Xception, which is one of the most popular image classification models resulted in 62.32% accuracy. The ResNet50V2 outperformed the other Keras API models, where it gave an accuracy of 76.55% on a sample database consisting of fewer images of the actual dataset.

4. RESULT ANALYSIS

In this study, the Lesion Melanoma Classification problem was addressed using deep learning techniques. A ResNet50v2 model was trained and validated on a dataset of skin lesion images. The preprocessing of the data was done by converting image IDs to image file names and sampling the data. The images were then scaled to have pixel values between 0 and 1, and the data were divided 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 increase the size of the training set and prevent 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 model was compiled using the categorical cross-entropy loss function and the Adam optimizer.

The model was trained for 10 epochs, and its accuracy was monitored during the training process. The final validation accuracy achieved was 80.14%, which indicates that the model was able to correctly classify the skin lesion images into one of the seven classes.

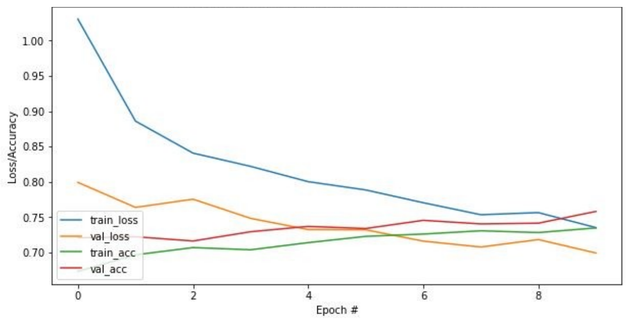

Figure 3. Training Loss and Accuracy on dataset - ResNet50v2

5. CONCLUSION:

In conclusion, this study showed the application of deep learning methods to the classification of 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 needed to evaluate the model's performance on other datasets and in real-world scenarios. 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.

ACKNOWLEDGMENTS

We express our deep sense of gratitude to our respected and learned guide, Dr Prof. Anupama Budhewar, for her valuable guidance and mentorship throughout this project, and we are thankful to her for the encouragement she has given us in completing this project. We are also grateful to all the faculty members of the Department of Computer Science and Engineering, MIT School of Engineering, for giving us this wonderful opportunity to learn and grow while working on this project.

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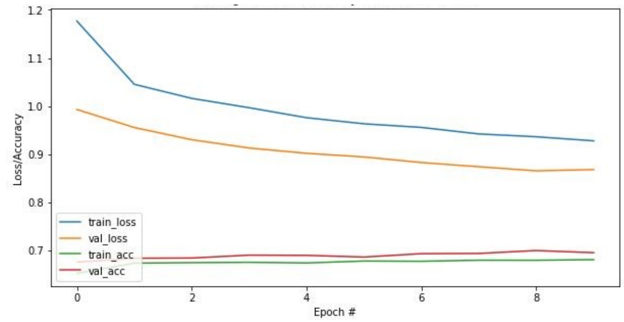

Figure 4. Training Loss and Accuracy on dataset - VGG16

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