



A Novel Approach to Detecting Melanoma Using Deep Learning

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Melanoma is the deadliest type of skin cancer and is the fifth most common cancer in the United States (Patel et al., 2022). If untreated, melanoma can spread to other parts of the body, such as organs or lymph nodes, drastically decreasing the survival rate (MacGill, 2019). Melanoma can be caused by many different internal factors such as age, number of moles, and genetics (MacGill, 2019). However, avoiding overexposure to UV radiation is one of the few risk factors that can be controlled, significantly lowering the risk of skin cancer (MacGill, 2019). The detection of melanoma in-situ has a survival rate of 99%, while stage IV melanoma has a survival rate of only 18% (Venosa & Kleiman, 2021). Therefore, the earlier one detects the symptoms of melanoma, the higher chances of a patient being cured (Kadampur, 2019). However, in 2020, there were 57,043 deaths worldwide, largely because of the lack of early detection (Patel et al., 2022).

METHODS TO DIAGNOSE MELANOMA

Dermoscopy is used for the screening of melanoma, which uses a specific criterion such as the ABCD rule or the Menzies method for analyzing irregular dots, streaks, and blotches (Feng, 2019). Next, biopsies are used to take samples of the suspected skin for examination in a laboratory (MacGill, 2019). However, melanoma is often left untreated. People avoid seeking treatment as biopsies are expensive, too far away, too inconvenient, and require a referral from a family doctor. At the Skin Cancer Screening Clinic (2022), biopsies can cost \$55 - \$175, with regular checkups leading to early diagnosis. Also, biopsies can take 1-2 weeks to get results (Gardner, 2020). This can be critical to one's survival rate, as it can take only 6 weeks for melanoma to become life-threatening (Better Health Channel, 2022).

RATIONALE AND HYPOTHESIS

Developing a deep learning algorithm to determine whether the lesion is melanoma or not, would provide an alternative to biopsies that has no costs with instant results. In addition, it may be used by clinics for a more thorough diagnosis of melanoma. There has been much research done on melanoma and deep learning. The Khulna University of Engineering & Technology (Rasul et al., 2020) utilized deep learning architectures such as ResNet500, Xception, VGG16, and InceptionV3 with accuracies of 95%, 96%, 94%, and 95% respectively. My supervised deep learning algorithm utilizes MobileNet V2, which through many processes, would be able to predict melanoma at 99% accuracy. Furthermore, the goal is to make a lightweight web application accessible on all devices where users would be able to upload images of their moles into the deep learning model to accurately provide a diagnosis in the comfort of their homes.

METHOD AND MATERIALS

DATASET

The HAM10K dataset from Kaggle was used to train my deep learning model, which is a large collection of multi-source dermatoscopic images of common pigmented skin lesions (Kaggle, 2018). By using various images in my sample dataset, my deep learning algorithm would be able to find patterns in melanoma-positive skin to predict melanoma in new images and datasets. The dataset consisted of 8,903 melanoma images and 8,902 non-melanoma images. The dataset was partitioned into three separate folders for training, testing, and validation. 60% of this data will be used in the training process for the deep learning model.

PREPROCESSING

Images were zoomed in, rotated, and reflected for data augmentation. Other data augmentation techniques that I used were vertical shifting, horizontal shifting, and shearing. The deep learning algorithm will need to adjust to different picture sizes, orientations, and qualities, as it will need to crop or resize the image and address all these possible impacts so that it can be processed correctly.

MOBILENET V2 ARCHITECTURE

After pre-processing, images were resized to 224 by 224 by 3 for the implementation of MobileNet V2 and TensorFlow 2 Saved-Model. MobileNet V2 allows for my deep learning model to be lightweight, almost twice as fast as MobileNet V1 (Holleman, 2019). Due to RGB pixel values ranging from zero to two hundred fifty-six, they were divided by two-hundred fifty-five for normalization so that the color values ranged from 0-1, allowing for faster computation (Ponraj, 2021). Then, the convolutional neural networks were customized into batch sizes of 16 with randomized pre-processed images.



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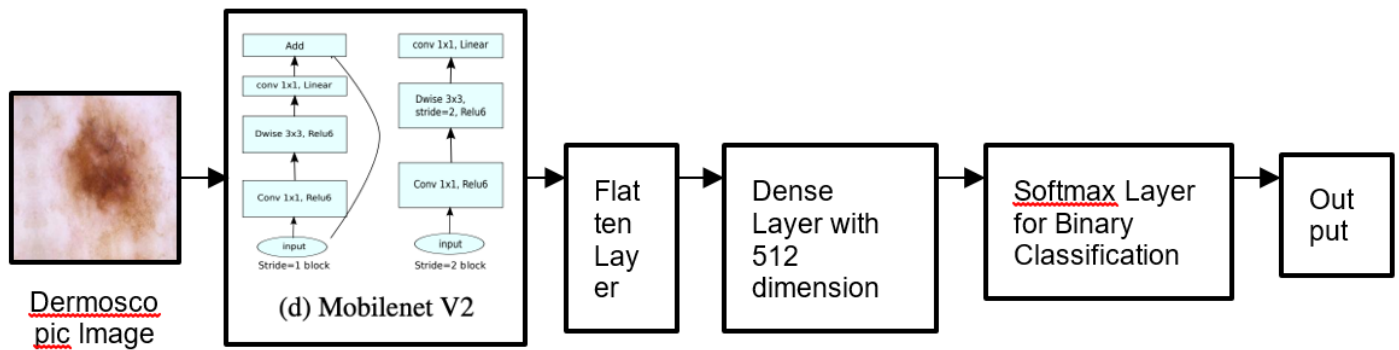


Figure 1: Deep Learning Model Architecture (Sandler et al., 2018).

CNN MODEL ARCHITECTURE

The deep learning model architecture consisted of the Keras Layer, exported from MobileNet V2, in addition to a series of hidden and output layers shown in Figure 1. The MobileNet V2 architecture consisted of inverted bottleneck residual blocks and lightweight convolutional layers. The residual bottleneck consisted of a point-wise convolution to expand features, depth-wise separable convolution, and point-wise convolution to reduce features (Tajbakhsh, 2020). MobileNet V2 also uses linear inverted bottlenecks that use linear activation functions for memory efficiency (Tajbakhsh, 2020). After, data is passed into a flatten layer, which is then inputted into a reLU dense layer with 512 neurons for a lower training loss. A Dropout Layer was used at 20% to reduce overfitting. Finally, the melanoma prediction was made using a softmax layer for binary classification. A confidence interval was also calculated using Numpy to distinguish between strong and weak melanoma predictions.

The dermoscopic image is passed into the MobileNet V2 Architecture as the input. After, the Flatten Layer converts the output from MobileNet V2 into a 1-dimensional array to be inputted into the Dense Layer, which classifies the image through Softmax and outputs 1 or 0, representing non-melanoma and melanoma respectively.

TESTS AND EXPERIMENTS

The batch size, steps per epoch, and epochs were tested to find the best accuracy. The initial training model had a batch size of 16, 10 steps per epoch, and 15 epochs. Through changing the steps per epoch from 10 to 455, which is the train dataset length divided by the batch size, there was an increase of 0.5% in accuracy. By changing the epoch value from 15 to 25, there was no change in accuracy. After training, Scikit-learn and Matplotlib were used to create a confusion matrix using the validation dataset as seen in Figure 2.

In Figure 3, Streamlit and Flask-Ngrok were used to create a web application for users to access the deep model. Input images were pre-processed and downloaded into Google Cloud. The image was converted into an array using OpenCV and then

passed into the deep learning model to provide a prediction and confidence rate. All modeling was performed using TensorFlow and Keras on a Windows Intel Core i3 processor.

OBSERVATIONS AND RESULTS

The deep learning model had an accuracy of 99.04%, with 455 steps per epoch, a batch size of 16, and 15 epochs. From analyzing the evaluation metrics in Figure 4, there was 98% precision for melanoma, 100% precision for non-melanoma, 100% recall for melanoma, 98% recall for non-melanoma, and 99% for both f1-scores. The evaluation metrics, such as the f1-score which provides the mean of how precise and accurate the results were, are essential to validate the accuracy of the deep learning model, The number of epochs remained the same throughout these tests, as I decided that fifteen epochs were a reasonable amount.

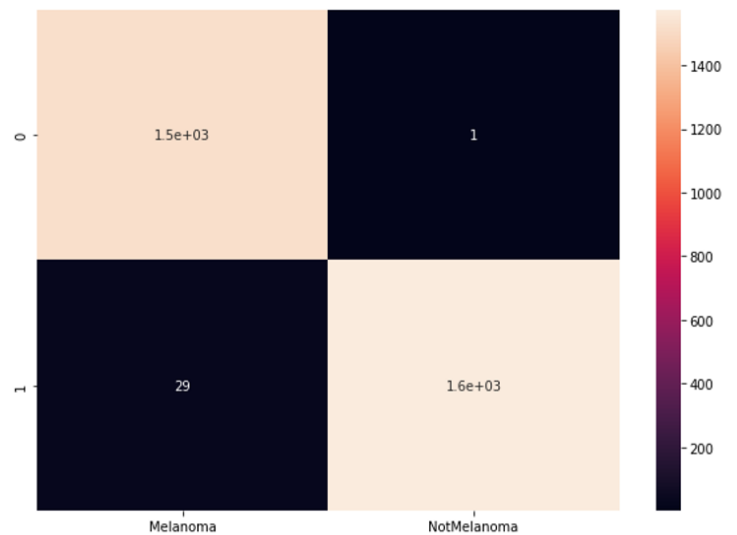


Figure 2: The Confusion Matrix represents the correctly and incorrectly predicted melanoma and non-melanoma images.



Melanoma Detection

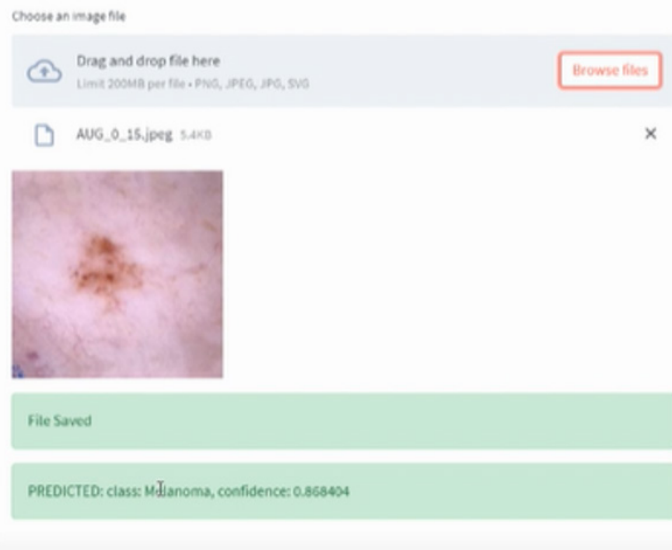


Figure 3: Streamlit Web Application predicts a melanoma dermoscopy image correctly at an 87% confidence level.

DISCUSSION

The process of image processing through Keras’ neural networks is efficient as MobileNet’s runtime and memory usage is adequate and lightweight for optimization of phones and computers in a practical environment, such as labs and hospitals. A prediction is generated through convolutional neural networks created using Keras Layers. It is accessible through a web app, allowing for ease of access while displaying a confidence level. This application can have large global impacts in both developed and developing coun-

tries, due to its accessibility and ease of use. It offers a cheap alternative to biopsies and enables the development of open access melanoma scans on a global scale. While it is useful for everyday people, it also provides practical usage at hospitals for an earlier and more accurate diagnosis of melanoma, advancing the fields of dermatology and anatomical pathology.

CONCLUSION

Overall, this study aimed to detect and diagnose melanoma that is accessible through a web application. It was concluded that the deep learning model could achieve this by developing a convolutional neural network using TensorFlow and Keras at a 99% accuracy rate.

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Classification Report				
	precision	recall	f1-score	support
Melanoma	0.98	1.00	0.99	1521
NotMelanoma	1.00	0.98	0.99	1602
accuracy			0.99	3123
macro avg	0.99	0.99	0.99	3123
weighted avg	0.99	0.99	0.99	3123

196/196 [=====] - 142s 725ms/step - loss: 0.0417 - accuracy: 0.9904 [0.04171403497457504, 0.990393877029419]

Figure 4: Classification Report of Deep Learning Model. The precision represents the number of correctly classified melanoma images from the total number of correctly and incorrectly predicted melanoma classified images. The recall represents the number of correctly classified melanoma images from the correctly predicted melanoma images and incorrectly predicted non-melanoma classified images. The F1 score is the mean of the precision and recall while support represents the number of melanoma occurrences in the dataset (Kharwal, 2021).



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Derek Sheen is a student researcher and software developer located in Waterloo, Ontario. Derek has been passionate about science and technology since he was 7 years old, creating many cool projects using mobile development, websites, and machine learning. Derek is always striving to learn new skills in the field and participate in opportunities that make positive impacts locally and globally. Some of Derek's hobbies include playing the violin and exercising with friends. Furthermore, Derek loves to compete in various math contests and has ranked top in many of them!

