Hardware Efficient Eye Tumour Detection System using Deep Learning

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Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Dated: 12/05/22 Aakash Agarwal

Certificate

This is to certify that the project titled "Hardware Efficient Eye Tumour Detection System using Deep Learning" by Aakash Agarwal" has been carried out under my/our supervision and that this work has not been submitted elsewhere for a degree/diploma.

Dated:12/05/22

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Aakash Agarwal

ABSTRACT

Eye melanoma is a rare disease but according to malignancy, it is the most common type of cancer. Just like other types of cancers, it is curable for most of the cases if diagnosed properly but the process of diagnosis is quite challenging and is the most problematic issue in the treatment of eye melanoma. This paper presents an automated eye melanoma detection method using a convolutional neural network (CNN). 244 pre-diagnosed samples are taken from a standard database followed by pre-processing to lower resolution samples and finally fed to the CNN architecture. The proposed work eliminates separate feature extraction as well as the classification for the detection of eye melanoma. A high accuracy rate of 97.40% is achieved outperforming the eye melanoma detection using an artificial neural network (ANN). We have also developed a android application and this model is deployed on it. We see a reduction of atleast 2 times in the model size using the post quantization technique.

Contents

1 Introduction

Eye Melanoma is one of the most deadly phases of cancer [1-2]. According to the National Cancer Institute (NCI), the young adult age group is the common victim of carcinoma, a form of eye melanoma. Though this form of cancer is a common cause of malignancy, ocular or eye melanoma is the rarest among all. 95% of cases there is a high chance of survival for patients if diagnosed at a very early stage of melanoma. But detection of this disease is just as difficult and rare as ocular melanoma is. The melanocytes present in the choroid, iris or ciliary body leads to this type of malignancy. The posterior choroid faces almost 85% of these cases. The iris, ciliary body and choroid anterior are directly related to the Anterior Uveal melanoma. Studies reveal that almost 50% of patients who are diagnosed with Uveal melanoma develop metastasis which makes this carcinoma a bleak malignancy even after treatment. The manual process of diagnosis of uveal melanoma needs very well trained specialists of high observation skills. Thus the diagnosis suffers from the variance.

2 Literature Survey

Ahmed et al.[1] have presented an eye melanoma detection system using ANN taking image features into account and obtained an accuracy of 85%. This was one of the first works that was done related to eye melanoma. The accuracy is too low to be deployed on an edge device. This work laid the foundation of other works. In [2], the authors have proposed a deep learning framework for Eye melanoma Detection using the Convolutional Neural Networks. They have shown an accuracy of 91.76%. Even though the accuracy surpassed the then state-of-the-art accuracy, it is still very low. Also, this method requires a lot of image processing and is hence not suitable for edge deployment. Very recently, the authors in [3] proposed another eye tumour detection method using deep learning. They have used the Hough transform to predict the eyeball and the iris region. They achieve a state-of-the-art accuracy of 95%. Even though the accuracy is pretty good but the computational cost of this method is very high which makes this system not implementable on a mobile device.

In our work, we have proposed an end-to-end eye tumour detection system. We have created a deep learning model which achieves an accuracy of 97.40%. We see that our system surpasses state-of-the-art accuracy. Apart from this, we develop an android mobile application for real time eye tumour detection.

3 Proposed Methodology

We have proposed a method to detect eye cancer from an eye image using mobile phone. This detection is done using the Convolutional Neural Networks. First of all we will record an eye image using the camera of the mobile phone, Then image processing techniques are applied, like cropping the image to 150 size. After the sample is ready to use, we feed the image directly to the deep learning model which gives us the probabilities to which class the image belongs.

Our solution is divided into 2 phases. The first phase is creating a deep learning model that could classify the incoming eye images. For this we use the keras library in python. After the deep learning model is obtained we have to reduce the size of this model and reduce the complexity so that this model can be deployed on an edge device, (mobile phone in our case). After the model is compressed it is deployed on a mobile application that we have developed

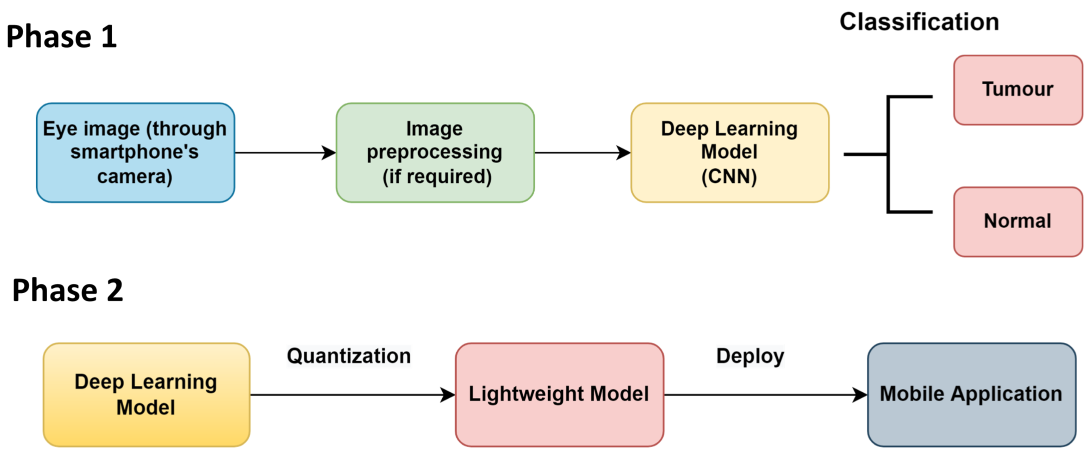

Figure 1: The proposed methodology for mobile based eye cancer detection

4 Dataset

Images of eye melanoma have been taken from New York Eye Cancer Center database. Each image is assessed and verified by medical experts that whether the images portray eye melanoma or not. We have obtained 244 images containing 128 cancerous images and 116 normal images.

Figure 2: Ocular images with choroidal melanoma obtained from []

5 Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.

EffecientNetV2

The version 2 of EfficientNet [4] identifies inefficiencies in the architecture and scaling strategies of the original EfficientNet. The modified NAS algorithm utilizes the prior knowledge of EfficientNetV1 and enables the adaptive search of efficient blocks and important hyperparameters. The searched architecture conveyed consistent and significant patterns that provide insights about efficient CNN architectures, which should be utilized when designing network architectures. The compound scaling strategy is slightly modified for parameter and memory efficiency. The modified progressive learning algorithm coupled with improved network architecture boosts the training speed of EfficientNetV2 by 11x compared to the baseline V1 network when achieving similar accuracies with the same computing power. Fig. 3 shows the model architecture of the EfficientNetV2.

Stage	Operator	Stride	#Channels	#Layers
0	Conv3x3	2	24	1
1	Fused-MBConv1, k3x3	1	24	2
2	Fused-MBConv4, k3x3	2	48	4
3	Fused-MBConv4, k3x3	2	64	4
4	MBConv4, k3x3, SE0.25	2	128	6
5	MBConv6, k3x3, SE0.25	1	160	9
6	MBConv6, k3x3, SE0.25	2	256	15
7	Conv1x1 & Pooling & FC	-	1280	1

Figure 3: The EfficientNetV2 Model Architecture

6 Model Size Reducton

Since our model is heavyweight and not suitable for deployment on an edge device (in our case, mobile) we try to reduce the size of the model. For reducing the model size we have used the quantization technique. Quantization helps in reducing the model size as well as providing upto 3x lower latency with a little degradation in model accuracy. Quantization quantizes weights to 8-bits of precision from floating-point.

7 Model Training Parameters

The deep learning model is developed using the open source library, tensorflow. The model is trained on a RTX 3070 GPU with 8GB RAM. Below are the parameters of the model training phase,

Parameter	**Value**
Loss Function	Categorical Cross Entropy
Optimizer	Root Mean Squared Propagation
Learning Rate	0.0001
Number of Epochs	10
Activation Function	Rectified Linear Unit (ReLU)

8 Results

Deep Learning Model

For training we use 80% of the data and for testing we use the rest of 20% data. We achieve a training accuracy of 96.97% and a testing accuracy of 97.40%. These accuracies are greater than the state-of-the-art work right now.

Table 1: Accuracy of the model in training and testing phase

Training Accuracy	96.97%
Testing Accuracy	97.40%

Fig 2, shows the confusion matrix of the proposed deep learning model. Various classification metric are calculated and presented in Fig.5

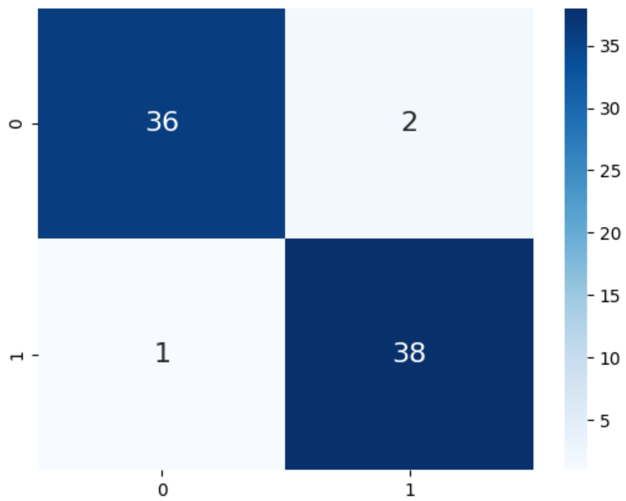

Figure 4: Confusion matrix of the deep learning classifier

Class	Precision	Recall	F1-Score	Support
Normal	0.97	0.95	0.96	40
Disease	0.95	0.97	0.96	37

Figure 5: Various classification evaluation metric

Mobile Application

We have created an android mobile application in android studio platform. The application takes in an image and shows to which class the image belongs to. After deploying our deep learning model we see an accuracy drop of mere 1.30%. We must also note that only 3 misclassification are happening out of all the 77 test files.

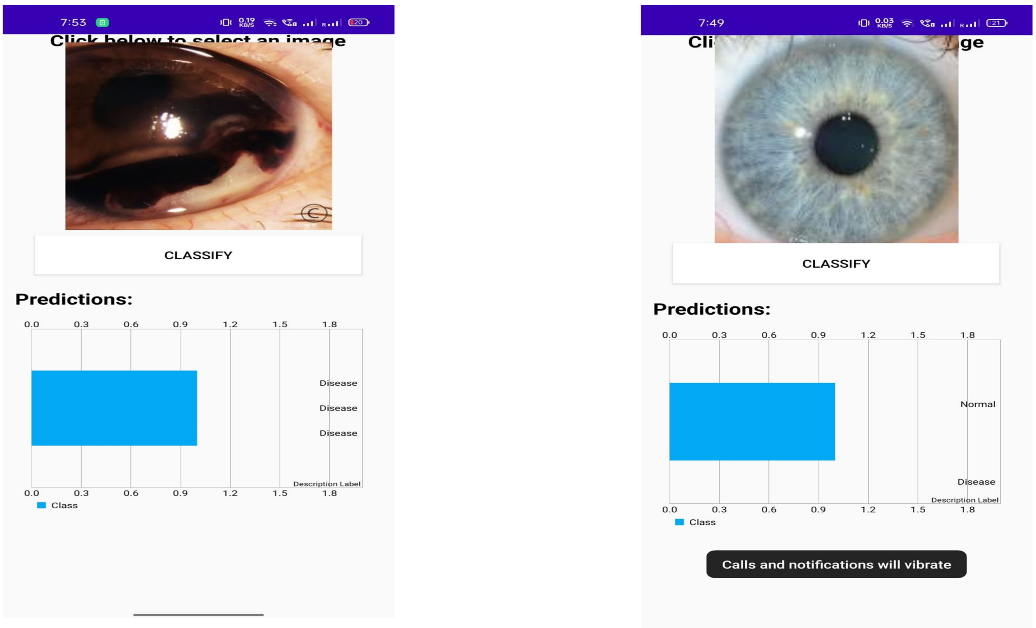

Figure 6: The mobile application. 1) Figure on the left hand side shows a normal eye classification. 2) Figure on the right hand side shows a cancerous eye classification

9 Conclusion

A deep learning model is created that achieves a training accuracy of 96.97% and a testing accuracy of 97.40This model is further reduced in size by using the post quantization technique. We have also created a mobile application that would detect eye tumour in real time.

References

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