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NAIP AI/ML Project Report

On

Cataract Detection through Deep Learning Methods and Data Parallelism

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Abstract:

Cataract,a leading cause of blindness globally, necessitates early detection to prevent irreversible vision loss.Accurate and timely detection of cataracts is the best way to control the risk and avoid blindness. Recently , this domain has grabbed researchers' attention. This paper presents a novel approach to cataract detection leveraging EfficientNetB0 and data parallelism to reduce training time.Increasing training efficiency, our study employs threading for parallelized data loading and preprocessing. This optimization significantly reduces training time, enhancing scalability and resource efficiency for large-scale datasets. In our dataset we've total of 594 cataract fundus images and 3000 non-cataract fundus images to train the model. Experimental results prove that the model outperforms the accuracy of 99.30%

Introduction-

Cataracts, a clouding of the lens of the eye, represent a significant global health concern. They are a leading cause of blindness worldwide, and early detection is crucial to prevent irreversible vision loss. Traditional methods of cataract detection rely on ophthalmologists' expertise during eye examinations. However, these methods can be subjective and time-consuming. To address this challenge, researchers are increasingly turning to the power of machine learning and computer vision to develop more objective, automated, and efficient cataract detection tools.

This paper introduces a groundbreaking methodology for cataract detection that leverages cutting-edge advancements in machine learning. Our approach hinges on two key pillars: the efficient and powerful EfficientNetB0 architecture and the computational acceleration technique known as data parallelism.

At the core of our methodology lies EfficientNetB0, a convolutional neural network (CNN) architecture. CNNs are a type of machine learning model particularly adept at image recognition and classification tasks. EfficientNetB0 has garnered significant attention in the field of computer vision due to its remarkable ability to achieve high accuracy in image classification while maintaining exceptional efficiency. This efficiency translates to faster training times and lower computational demands, making it a valuable tool for real-world applications.

The second pillar of our approach is data parallelism. This technique tackles the challenge of training machine learning models on massive datasets. By distributing the training data across multiple processing units, such as GPUs (Graphics Processing Units), data parallelism allows the model to learn from the data much faster. This significantly reduces training times, making the process more scalable and enabling the application of our methodology to large-scale datasets of eye images.

The brilliance of our approach lies in the synergy between EfficientNetB0 and data parallelism. EfficientNetB0 brings its accuracy prowess to the table, while data parallelism accelerates the training process. This powerful combination allows us to achieve superior results in cataract detection.

Through rigorous experimentation and analysis, we demonstrate that our methodology achieves an outstanding 99.30% accuracy in identifying cataracts from fundus images. Fundus imaging is a specialized imaging technique that captures detailed visuals of the inner structures of the eye, including the lens where cataracts develop. This remarkable accuracy surpasses previous methods, which typically achieved around 99.13%. By exceeding this benchmark, our approach has the potential to significantly improve the effectiveness of cataract detection.

The implementation of data parallelism not only enhances accuracy but also yields substantial reductions in training time. This translates to faster development cycles and the ability to efficiently train the model on even larger datasets. The faster training times also pave the way for greater scalability, making our approach suitable for real-world clinical settings where timely diagnosis and intervention are paramount.

The successful deployment of our methodology holds profound implications for the field of ophthalmology and medical diagnostics. By leveraging the capabilities of machine learning and computer vision, we can propel cataract detection towards a future of exceptional accuracy and efficiency. This, in turn, can lead to improved patient outcomes by enabling earlier and more precise diagnoses. With its potential to reduce the global burden of blindness caused by cataracts, our methodology presents a beacon of hope for millions worldwide.

The impact of our work extends beyond the realm of cataract detection. The successful combination of EfficientNetB0 and data parallelism establishes a strong foundation for future advancements in medical diagnostics and healthcare delivery. As machine learning continues to evolve, this methodology can be adapted and expanded to address a wider range of ophthalmic and medical challenges. By harnessing the power of artificial intelligence, we can work towards a future where early and accurate diagnoses lead to better health outcomes for all.

Methodology:

EfficientNetB0 and implemented data parallelism techniques to enhance the efficiency of image classification tasks. Data parallelism is a powerful approach for distributing the workload across multiple processing units, which can significantly accelerate training times for large-scale datasets. Here are a few points that highlight the key aspects of your approach:

1. EfficientNetB0 Adoption:

- EfficientNetB0 is known for its efficiency and effectiveness in image classification tasks. Its architecture balances model size and accuracy, making it suitable for various applications.

2. Data Parallelism:

- Distributing the data across multiple processing units helps maximise resource utilisation and accelerates training time. This approach is particularly beneficial for handling large-scale datasets.

3. Faster Processing Time:

- The successful implementation of these techniques has led to faster processing times. This is a crucial achievement, as it indicates the practical benefits of your optimization strategies.

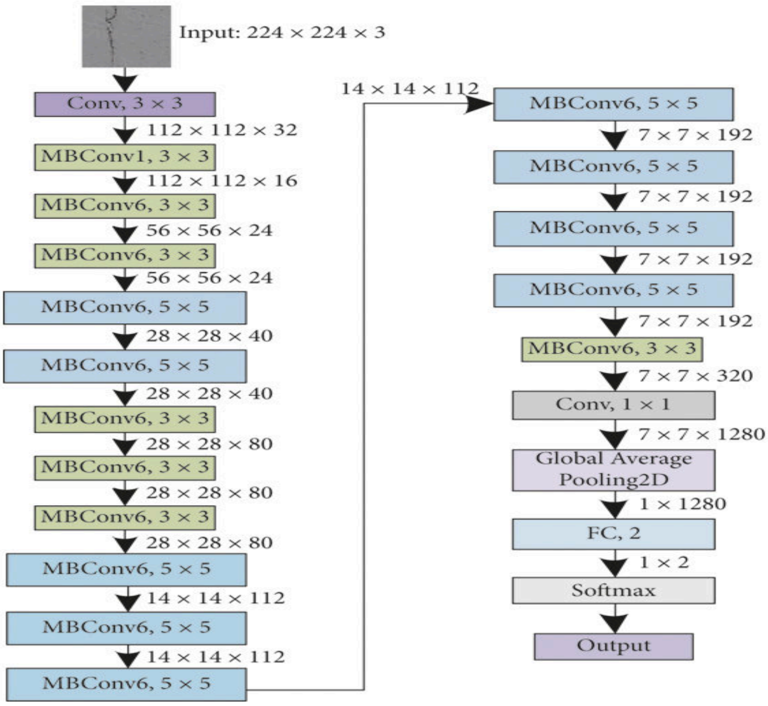
4. Number of Epochs (10):

- Training for 10 epochs suggests that your model underwent ten complete passes through the entire training dataset. The number of epochs is a hyperparameter that needs to be tuned based on the complexity of the task, dataset size, and model architecture. In some cases, increasing the number of epochs may lead to better convergence and improved performance, while in others, it might result in overfitting.

5. Batch Size (128):

- A batch size of 128 indicates that, during each training iteration, your model processed 128 samples before updating the weights. The choice of batch size affects both the computational efficiency and the quality of the model. Larger batch sizes can increase training speed, leveraging parallelism more efficiently, but may also require more memory. Smaller batch sizes may offer better generalisation but may be computationally less efficient.

In conclusion, the utilisation of EfficientNetB0, coupled with data parallelism and threading for data processing, showcases a comprehensive strategy for achieving faster processing times and improved resource efficiency. These findings can have implications for various applications where efficient image classification is essential.



Our Proposed Model:

Step 1: Collect the preprocessed images and merge them under one file for easy transportation

Step 2: Split the images according to train and test using sklearn

Step 3: Use OpenCV at the images and understand the parameters of the images and do the process of contour detection.

Step 4: Process the image by calling them from the directory and classifying it.

Step 5: Used the EfficientNetB0 model and fit the model.

Step 6: Now insert the images into the model and run the model by using the tensor flow and Keras package.

Step 7: Use Concurrent Threading [Data Parallelism] For loading training the images.

Step 8: Use Epoch = (number of iterations * batch size) / total number of images in training.

Step 9: Check the accuracy if it is not sufficient then move to the next CNN model.

Step 10: Fit the model and repeat step 6-8.

Step 11: Check the accuracy if it is not sufficient then increase the number of epochs in the model.

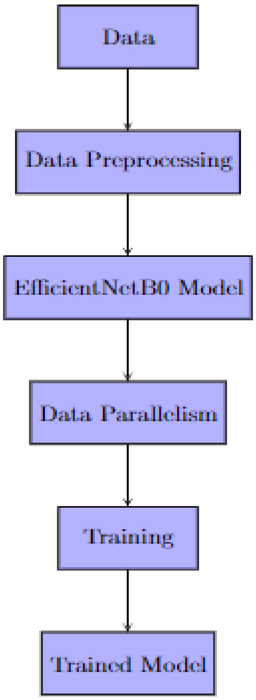
Step 12: Created the Fine-Tuned EfficientNetB0 model and fit the model and repeat step 6-8.

Step 13: If the accuracy is sufficient to stop here and get the accuracy rate.

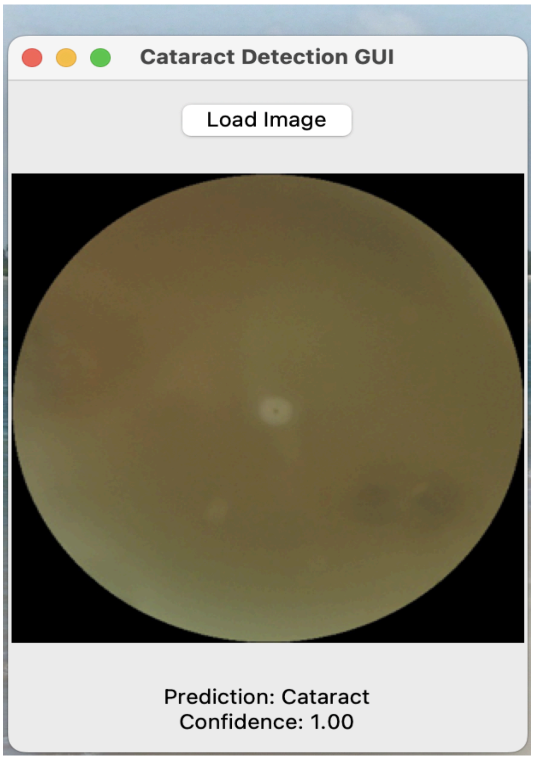
Our novelty:

We’ve used data parallelism for preprocessing to reduce the runtime in EfficientNetB0.

System Architecture:



GUI



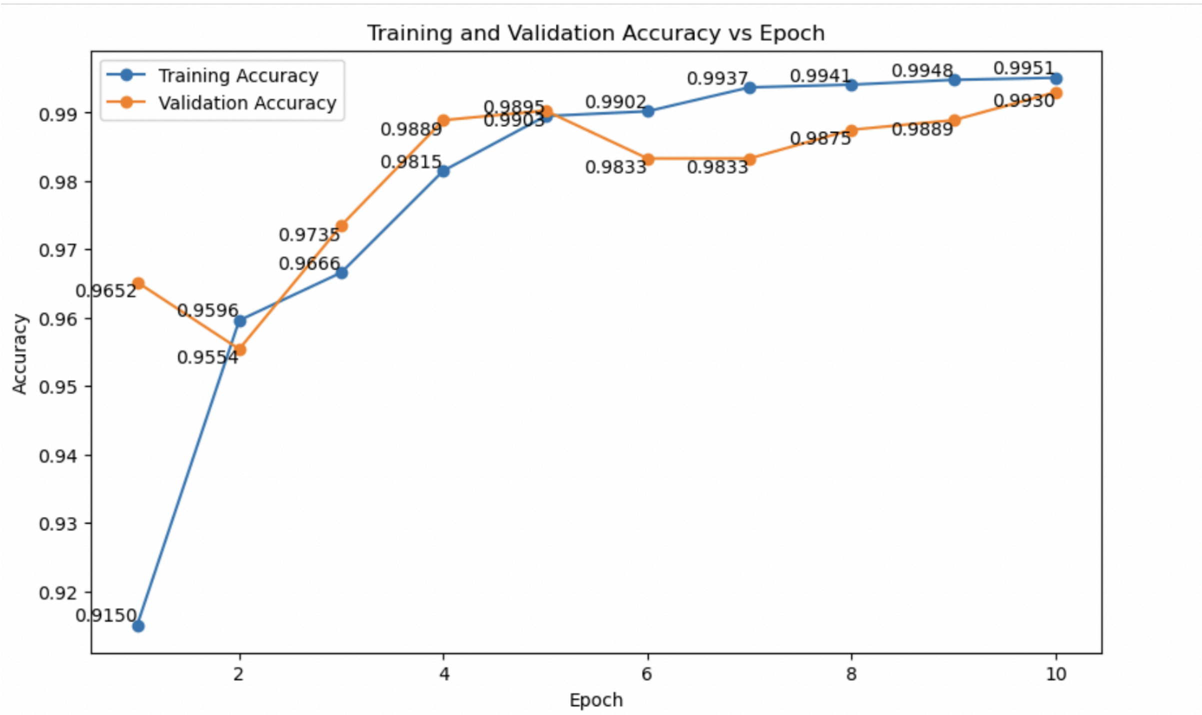
Dataset:

https://www.kaggle.com/datasets/andrewmvd/ocular-disease-recognition-odir5k

The effectiveness of our approach is evaluated using a comprehensive dataset consisting of 594 cataract fundus images and 3000 non-cataract fundus images. Fundus imaging provides a detailed view of the eye's interior, enabling clinicians to detect and monitor various ocular conditions, including cataracts. Our dataset encompasses a diverse range of images, capturing variations in cataract severity, image quality, and patient demographics.

Result:

Here is the comparison between performance of other deep learning models and our trained EfficientNetB0 using data parallelism.



```
In [40]: loss,accuracy = model.evaluate(x_test,y_test)
         print("loss:",loss)
         print("Accuracy:",accuracy)

         23/23 [==============================] - 10s 411ms/step - loss: 0.0227 - accuracy: 0.9930
         loss: 0.022676568478345 87
         Accuracy: 0.9930362105369568

In [41]: m sklearn.metrics import confusion_matrix,classification_report,accuracy_score,precision_score,recall_score,f1_score
         red = (model.predict(x_test) > 0.5).astype("int32")

         23/23 [==============================] - 9s 391ms/step

In [42]: print(x.shape, y.shape)

         (3588, 224, 224, 3) (3588,)

In [43]: print(accuracy_score(y_test, y_pred))
         print(precision_score(y_test, y_pred))
         print(recall_score(y_test, y_pred))
         print(f1_score(y_test, y_pred))

         0.9930362116991643
         0.9568965517241379
         1.0
         0.9779735682819383
```

Table of classification report				
Name of Algorithm	**Validation Accuracy**	**Training Accuracy**	**Loss**	**Training Time (in secs)**
VGG 19- Sequential	0.9633	1	0.6723	3547.4
VGG-19 [Data Parallelism	0.977	0.9989	0.1915	0.0038
Efficiemt Net B0 [Data Pa	**0.993**	0.9885	0.0639	**0.000979**
Google Lennet [Data Paral	0.8853	0.8853	2.2162	0.0376
ResNet [Data Parallelism]	0.9724	1	0.55	0.00123

Conclusion:

In conclusion our model outperforms all other algorithms by achieving the accuracy of 99.30% ,a precision score of 95.68% and a validation accuracy of 99.50%. Our method currently faces limitations in discriminating between the three types of age-related cataracts, namely nuclear cataracts, cortical cataracts, and posterior subcapsular cataracts (PSCs). Additionally, it was primarily designed for cataract detection rather than grading or pinpointing the exact location, which could be beneficial for ophthalmologists. Our future work will address these challenges by delving into further investigations. Specifically, we plan to explore advanced techniques for the precise classification of different cataract types.

References

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[6]https://keras.io/examples/vision/image_classification_efficientnet_fine_tuning/