IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Cataract Detection Through Deep Learning Methods

[1]Malay Jignesh Shah, [2]Saurabh Advani, [3]Priyanshi Jain, [4]Lavanya Singh, [5]Sayal Goyal, [6]Dr. Yogesh R Kulkarni

[1]Student, [2]Student, [3]Student, [4]Student, [5]Student, [6]Professor

[1]Computer Engineering and Technology

[1]MIT-WPU, Pune, India,

[2]Computer Engineering and Technology

[2]MIT-WPU, Pune, India,

[3]Computer Engineering and Technology

[3]MIT-WPU, Pune, India,

[4]Computer Engineering and Technology

[4]MIT-WPU, Pune, India,

[5]Computer Engineering and Technology

[5]MIT-WPU, Pune, India,

[6]Computer Engineering and Technology

[6]MIT-WPU, Pune, India,

Abstract: Cataract, a common eye condition characterized by clouding of the lens, remains a leading cause of vision impairment worldwide. Timely detection and intervention are crucial for effective management of this condition. In this project, we propose a novel approach for cataract detection leveraging deep learning methods techniques.In this project, we introduce a novel method for detecting cataracts using deep learning. We utilize the EfficientNetB0 model for its efficiency and robustness in image classification tasks and implement parallel processing with a ThreadPoolExecutor to optimize computational resources. Using the ODIR-5K dataset, we train and evaluate the model, achieving an impressive 96.80 % accuracy in cataract detection. Our results demonstrate the model's efficacy in distinguishing between normal and cataractous retinal images, offering a promising solution for early detection and intervention in cataract-related visual impairments.

Keywords: Deep learning, EfficientNetB0, Convolutional neural network (CNN), Image classification

I. Introduction

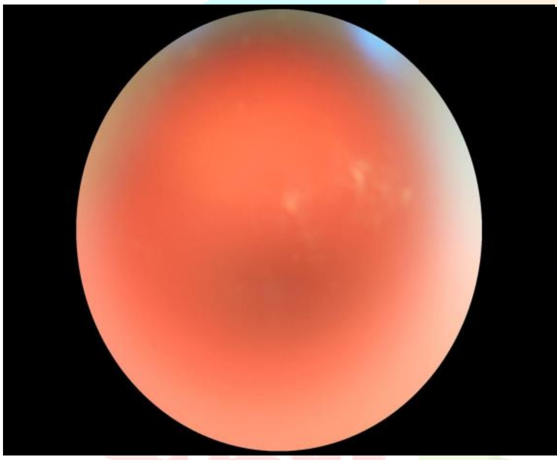
Cataracts, a clouding of the lens of the eye, represent a significant global health concern. They are a leading cause of blindness worldwide, and early detection is crucial to prevent irreversible vision loss. Traditional methods of cataract detection rely on ophthalmologists' expertise during eye examinations. 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 project introduces a groundbreaking methodology for cataract detection that leverages cutting-edge advancements in machine learning.

Our approach hinges on one key pillar: the efficient and powerful EfficientNetB0 architecture. 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.

EfficientNetB0 represents a breakthrough in the field of computer vision due to its exceptional balance between model size and performance. Its architecture is meticulously crafted to achieve optimal results while minimizing computational resources. This efficiency is particularly valuable in healthcare applications, where speed and scalability are essential for real-world deployment.
Fundus imaging, the technique we employ, provides a comprehensive view of the eye's inner structures, including the lens affected by cataracts. By analyzing these detailed images, our model can accurately identify the presence of cataracts with an impressive accuracy rate of 96.80%. This level of precision is crucial for early detection, enabling timely intervention to prevent irreversible vision loss and improve patient outcomes.

Furthermore, our methodology offers several advantages over traditional cataract detection methods. It provides an objective and standardized approach, reducing the subjectivity inherent in human assessments during eye examinations. Moreover, by automating the detection process, our model can significantly reduce the time and resources required for diagnosis, enabling healthcare professionals to focus their efforts more effectively.

In essence, our approach represents a paradigm shift in cataract detection, harnessing the power of machine learning and computer vision to enhance diagnostic accuracy, efficiency, and accessibility. As we continue to refine and expand upon this methodology, we envision it playing a vital role in improving eye health outcomes globally.



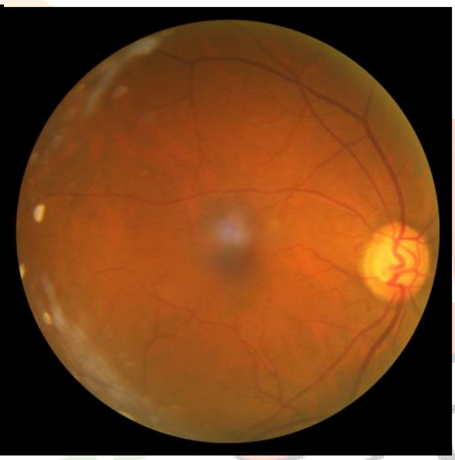


fig 1. Cataract Retina fig 2. Normal Retina

II. Related Work:

[1] This paper proposed a cataract detection system based on a 2D Gaussian filter and decision tree algorithm trained by 1355 retinal fundus images, which achieved an accuracy of 81.1% accuracy of exact cataract grading and 92.8% accuracy of two-class screening. [2] This paper proposed a deep convolutional neural network based approach trained by 5620 images after applying G-filter on retinal fundus images. The best accuracy achieved is 93.52% and 86.69% in cataract detection and grading tasks. [3] This paper proposed a discrete state transition (DST) and Res-Net based system. This system has achieved an excellent cataract detection performance (94.00%) and overcome the vanishing gradient problems.

[4] This paper proposed a DCNN approach with a random forest-based cataract classifier model. They trained the cataract detection system with 3460 retinal fundus images and tested on 1948 images achieving an accuracy of 95.04%. [5] This paper proposed a machine learning approach such as Support Vector Machine (SVM). In this system, the whole image is segmented into 17 parts and each part feeds to the SVM system. This approach obtained an accuracy of 87.52% but the partial cataract is not detected by their system. [6] This paper proposed an automatic cataract detection system using DCNNs and trained classifier model based on Res-Net, whose accuracy was 95.77%

III. PROPOSED MODEL

EfficientNetB0 techniques to enhance the efficiency of image classification tasks. 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. 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.

3. 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.

4. 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 generalization but may be computationally less efficient.

In conclusion, the utilization of EfficientNetB0 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.

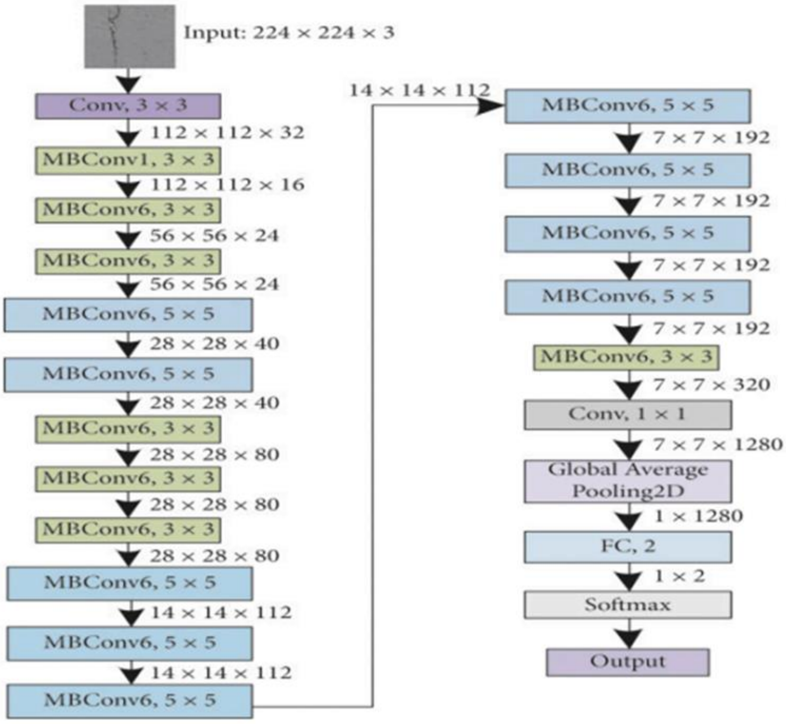


fig 3. EfficientNet B0 Architecture

IV. Pseudocode

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: Use 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: 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: Create 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.

V. SYSTEM ARCHITECTURE

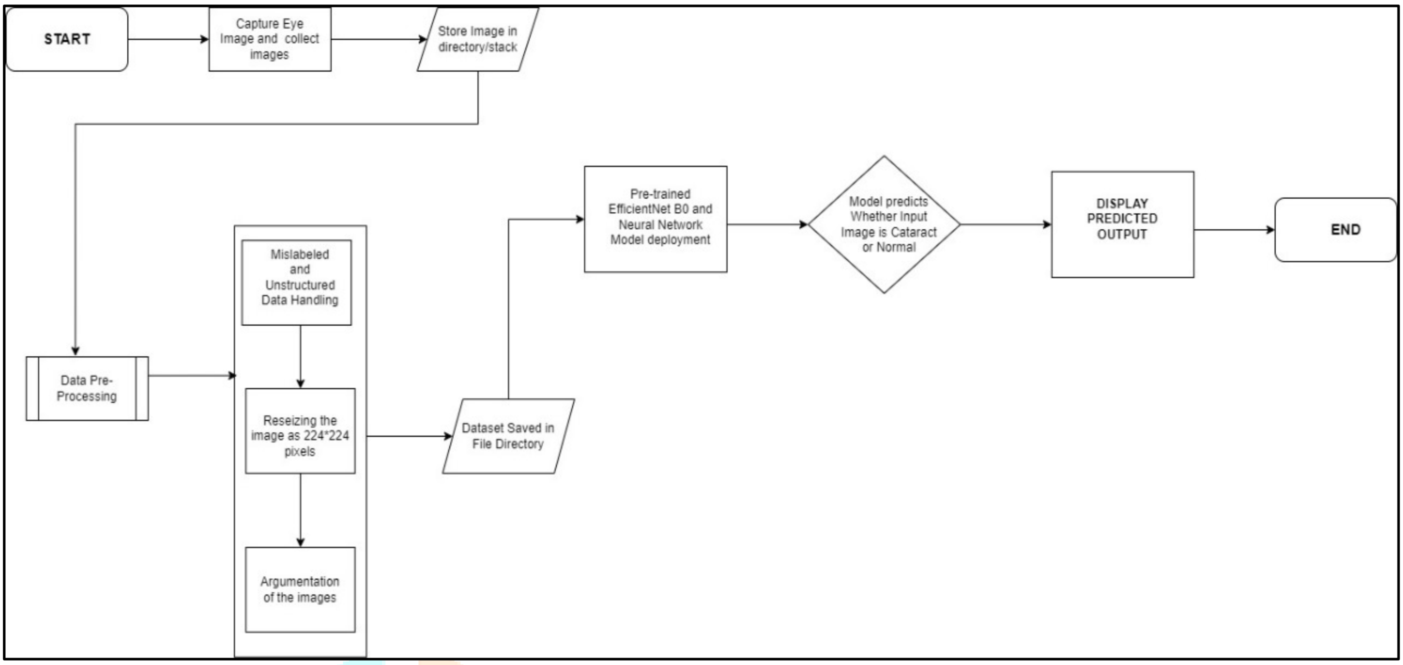


fig 4. System Architecture

VI. SIMULATION RESULTS

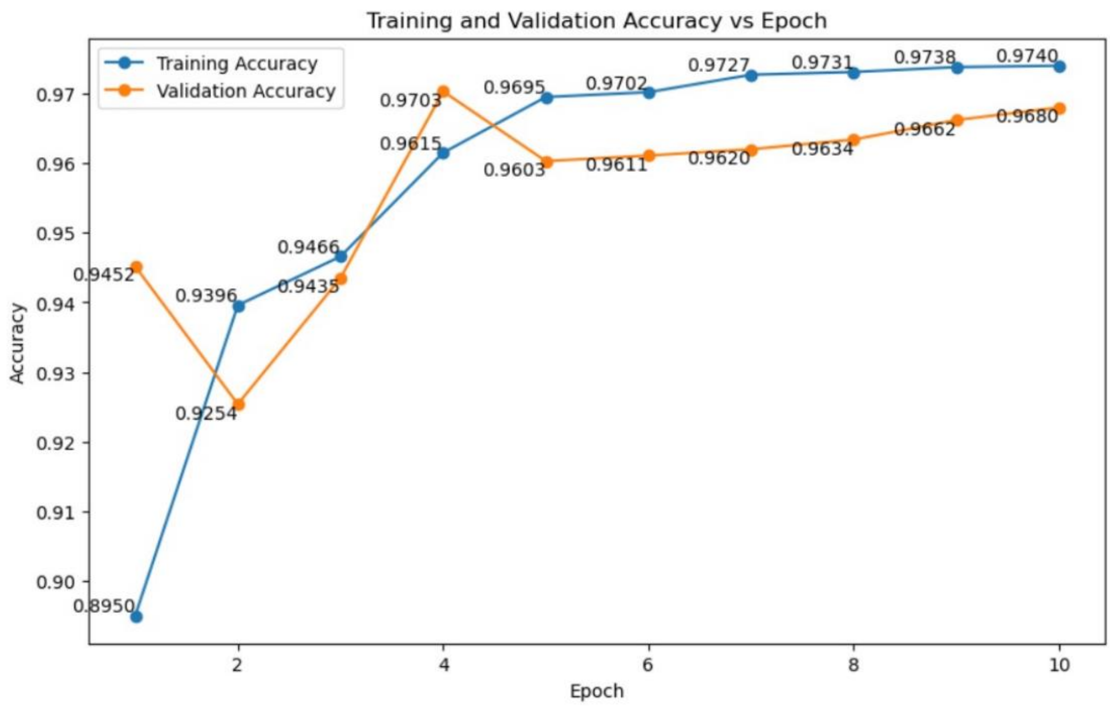


fig 5. Training v/s Validation Accuracy

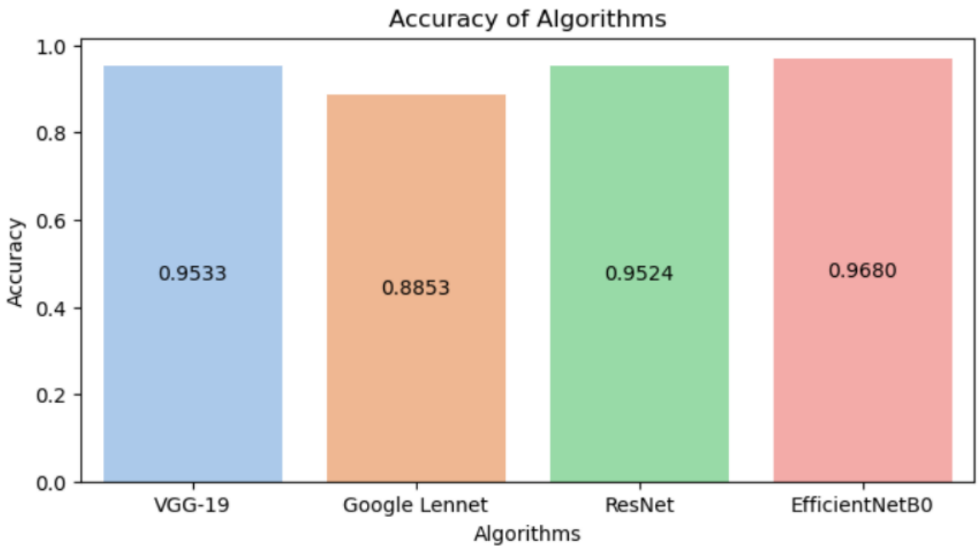


fig 6. Validation Accuracy Comparison Graph

Table of Classification Report

Name of Algorithm	Validation Accuracy	Training Accuracy	Loss	Training Time(in secs)
VGG-19 (Sequential)	0.9533	1	0.6723	3547.4
Google Lennet	0.8853	0.8853	2.2162	0.0376
ResNet	0.9524	1	0.55	0.00123
EfficientNetB0	**0.968**	**0.974**	**0.0639**	**0.000986**

fig 7. Comparison Table

VII. OUTPUT

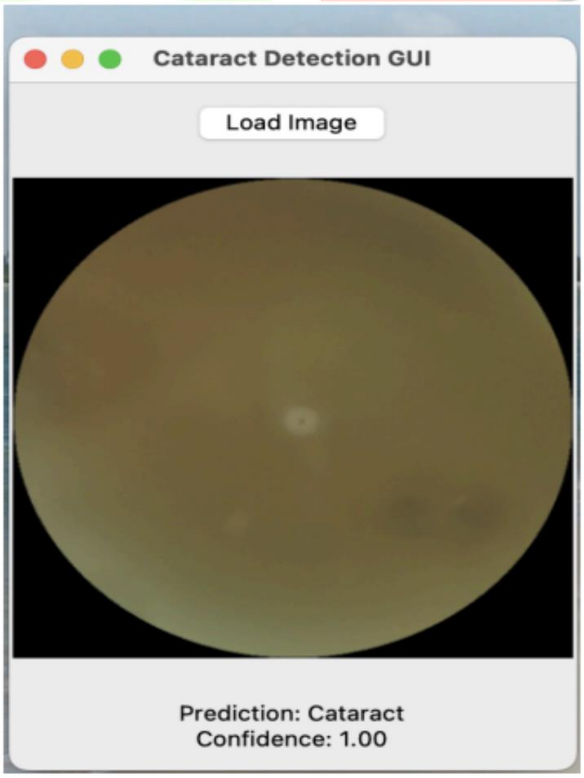


fig 8. Graphic User Interface

VIII. Conclusion and Future Work

In conclusion our model outperforms all other algorithms by achieving the validation accuracy of 96.80% , and a training accuracy of 97.40%. 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.

IX. References

[1] L. Xiong, H. Li, and L. Xu, “An Approach to Evaluate Blurriness in Retinal Images with Vitreous Opacity for Cataract Diagnosis” (Journal paper) (2017)

[2] Linglin Zhang et al.,“Automatic cataract detection and grading using Deep Convolutional Neural Network” (Conference paper) (2017)

[3] Y. Zhou, G. Li and H. Li,“Automatic Cataract Classification Using Deep Neural Network With Discrete State Transition” (Journal paper) (2020)

[4] J. Ran, K. Niu, Z. He, H. Zhang and H. Song, “Cataract Detection and Grading Based on Combination of Deep Convolutional Neural Network and Random Forests” (Conference paper)(2018)

[5] Z. Qiao, Q. Zhang, Y. Dong and J. Yang, “Application of SVM based on genetic algorithm in classification of cataract fundus images”(Conference paper) (2017)

[6] M. R. Hossain, S. Afroze, N.Siddique, and M. M. Hoque,“Automatic detection of eye cataract using deep convolutional neural networks (DCNNs)” (Journal) (2020)

[7] K. T. Ahmed, S. Jaffar, M. G. Hussain, S. Fareed, A. Mehmood and G. S. Choi, "Maximum Response Deep Learning Using Markov, Retinal & Primitive Patch Binding With GoogLeNet & VGG-19 for Large Image Retrieval," in IEEE Access, vol. 9, pp. 41934-41957, 2021, doi: 10.1109/ACCESS.2021.3063545.

[8] G. Shekar, S. Revathy and E. K. Goud, "Malaria Detection using Deep Learning," 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184), Tirunelveli, India, 2020, pp. 746-750, doi: 10.1109/ICOEI48184.2020.9143023.

[9] Journal Paper- Junayed, Masum Shah,Islam, Md Baharul,Sadeghzadeh, Arezoo, Rahman, Saimunur, PY-2021/09/15, “CataractNet: An Automated Cataract Detection System Using Deep Learning for Fundus Images”, 10.1109/ACCESS.2021.3112938, IEEE Access

[10] Meimei Yang, J. -J. Yang, Qinyan Zhang, Yu Niu and Jianqiang Li, "Classification of retinal image for automatic cataract detection," 2013 IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom 2013), Lisbon, 2013, pp. 674-679, doi: 10.1109/HealthCom.2013.6720761.