EYE DISEASE RECOGNITION SYSTEM

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Abstract : This paper presents an innovative system for detecting eye diseases utilizing advanced machine learning techniques. Given the increasing prevalence of eye disorders, early detection and intervention are of utmost importance. The proposed system integrates a diverse dataset comprising medical images and patient information. Deep learning algorithms are employed to extract intricate features from the dataset. These features are then input into a predictive model, facilitating accurate identification of potential eye diseases. Rigorous testing and validation demonstrate the system's performance and its ability to provide reliable predictions. The early diagnosis enabled by this system has the potential to significantly impact patient outcomes and contribute to the advancement of ophthalmic healthcare. The Eye Disease Detection System serves as a valuable tool for the early detection and management of various eye conditions. Through the integration of advanced technologies such as machine learning and medical imaging, this system enhances the accuracy and efficiency of the diagnostic process.

Index Terms : Vision disorders, Glaucoma, Macular degeneration, Eye diseases, Ophthalmology, Corneal diseases.

1. INTRODUCTION

A considerable portion of our country's population resides in rural areas, where access to medical services is scarce. In these regions, people often lack awareness about health issues, compounded by inadequate communication infrastructure. Globally, eye diseases are recognized as leading causes of nonfatal disabling conditions. In India, an estimated 4.95 million people are blind (0.36% of the total population), 35 million are visually impaired (2.55%), and there are 0.24 million blind children. Timely diagnosis remains a challenge, contributing to the prevalence of these conditions. Common eye diseases such as Cataracts, Glaucoma, Amblyopia, and Dry eye syndrome affect individuals across the country, particularly in rural areas where awareness is limited. Lack of understanding about these diseases leads to suffering among patients, and in some cases, incorrect diagnosis or treatment can result in permanent vision loss. Addressing this issue, an osteopathic expert system is proposed. This study focuses on a meticulously designed convolutional neural network (CNN) model for the recognition of prevalent eye diseases in India.

A diverse dataset of various eye diseases along with normal eye images was collected, followed by thorough pre-processing to enhance dataset size, diversity, and robustness. Two state-of-the-art CNN models, namely VGG16 and InceptionV3 were employed in the modeling process.

The widely used transfer learning approach, involving fine-tuning pre-trained networks, was adopted. Regardless of the training model nature, various pre-processing steps, such as image resizing, quantity adjustment, standardization, and enhancement, were applied to the image datasets. The impact of image quality on overall architecture performance was acknowledged, emphasizing the importance of image dataset quality in CNN model training. Hyperparameter tuning was conducted for each model, and their performances were compared using significant metrics like accuracy, precision, recall, and F1-score to determine the most suitable model for the task.

2. OBJECTIVE

In this research article, our primary objective is to surpass the accuracy, sensitivity, and specificity of existing deep learning models in the detection of early-stage Eye Diseases (ED). We employ a novel approach by combining traditional image processing techniques for image enhancement and segmentation, followed by training in deep learning algorithms. The paper emphasizes the significance of traditional image preprocessing in improving early-stage ED detection accuracy when utilizing deep learning models. It is crucial to note that the technological advancement discussed herein does not advocate for the complete replacement of ophthalmologists but rather aims to provide them with more reliable tools for ED diagnosis. The contributions of this paper in the realm of early ED diagnosis can be categorized as follows:

2.1 Image Enhancement*:*

Techniques such as green channel extraction, contrast-limited adaptive histogram equalization (CLAHE), and illumination correction are employed to enhance the original retinal fundus images.

2.2 Image Segmentation:

Regions of Interest (ROI) such as blood vessels, macular region, and optic nerve are segmented from the enhanced retinal fundus images.

2.3 Pre-trained Model:

High-performance models are selected for classifying the processed and segmented retinal fundus images.

2.4 Build a New CNN Model*:*

A new Convolutional Neural Network (CNN) model is constructed, and the model is trained from scratch using the processed and segmented retinal fundus images.

The complications associated with early ED in the retina include:

- Anatomical Structure of the Retina.
- Microaneurysms: Narrow bulges in blood vessels, particularly associated with diabetic retinopathy.
- Soft Exudates in Macula: Linked to diabetic macular edema.
- Optic Nerve Damage: Particularly associated with glaucoma.

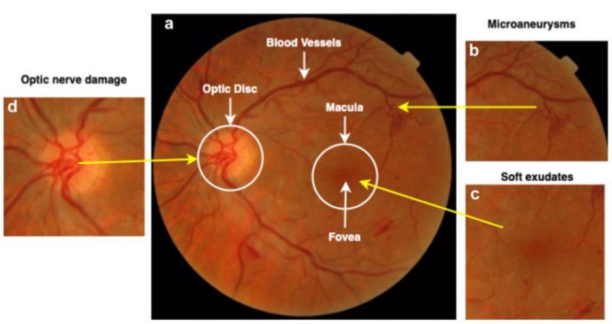


Fig 1. A Fundus Image of Eye

3. RELATED WORKS

The early detection of early eye diseases (ED) in retinal fundus images relies on a clinical technique that visualizes a comprehensive set of features and their localization within the image. Detecting ED is particularly challenging in diabetic patients during early stages, as it depends on the presence of microaneurysms (bulges in blood vessels), fluid leakage from blood vessels, formation of soft exudates, and optic nerve damage in retinal fundus images. To alleviate the burden on ophthalmologists and reduce diagnostic inconsistencies, automated ED diagnostics have been explored in previous studies, with a focus on lesion-based detection.

Followings are some of the Detailed description of related works-

In the research paper titled "Convolutional Neural Networks for Image Recognition" (2015) by Hijazi, S., Kumar, R. Rowen, the focus is on the utilization of Convolutional Neural Networks (CNN) for image recognition. The authors introduce the CNN module and implement it with specific algorithms, namely MNIST and CIFAR. The MNIST algorithm demonstrates an accuracy of 80.17%, indicating the model's proficiency in recognizing handwritten digits. Additionally, the CIFAR algorithm achieves a commendable accuracy of 76.57%, underscoring the effectiveness of the CNN approach in image recognition tasks. These findings suggest that the implemented CNN module, when applied to datasets like MNIST and CIFAR, yields accurate and reliable results, showcasing its potential for applications such as an Eye Disease Recognition System. The paper contributes valuable insights into the performance metrics of CNNs, providing a foundation for further exploration and refinement in the realm of image recognition and deep learning.

In the comprehensive review article titled "Deep learning in ophthalmology: a review" published in the Canadian Journal of Ophthalmology (Volume 53), Parampal S. Grewal, Faraz Oloumi, Uriel Rubin, and Matthew T.S. Tennant delve into the applications of deep learning in the field of ophthalmology. The authors thoroughly explore the capabilities and limitations of deep learning, providing a nuanced understanding of its real-life uses. The paper goes beyond theoretical aspects, offering insights into practical applications, thereby contributing valuable information to the domain of ophthalmic research. By addressing both the strengths and limitations of deep learning, the authors contribute to a more holistic view of its potential in ophthalmology. This review serves as a valuable resource for researchers and practitioners seeking to implement deep learning techniques in the development of systems like the Eye Disease Recognition System, offering a well-rounded perspective on the current state and future prospects of deep learning in ophthalmic applications.

The research paper titled "OverFeat: Integrated Recognition, Localization, and Detection Using Convolutional Networks" by Sermanet, Pierre, David Eigen, Xiang Zhang, and Michael explores advancements in computer vision through the integration of recognition, localization, and detection using Convolutional Networks (ConvNets) and a sliding window approach. The authors highlight the methodology of OverFeat, emphasizing its ability to perform integrated tasks seamlessly. The paper focuses on the utilization of ConvNets and the sliding window technique to enhance performance. Notably, the authors propose the use of L2 loss optimization as a means of further improving system performance. This innovative approach demonstrates a commitment to refining deep learning techniques for object recognition and detection. The findings contribute to the broader understanding of ConvNets and their applications, showcasing how specific optimization strategies, such as employing L2 loss, can lead to enhanced results in integrated recognition, localization, and detection tasks.

The research paper titled "Large-scale machine learning on heterogeneous distributed systems" (2016) by Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., and Corrado, explores the use of Tensorflow in large-scale machine learning on heterogeneous distributed systems. The authors delve into the capabilities of Tensorflow, a popular deep learning framework, and highlight its significance in addressing the challenges posed by distributed computing environments. The paper underscores the effectiveness of Tensorflow in facilitating machine learning tasks on diverse and complex systems. Specifically, it sheds light on the modules and algorithms employed within Tensorflow, showcasing their relevance to the development of advanced applications such as an Eye Disease Recognition System. The findings emphasize the potential of Tensorflow as a powerful tool for implementing deep learning models in complex, distributed settings, thereby contributing valuable insights to the broader field of machine learning and its applications.

4. METHODS

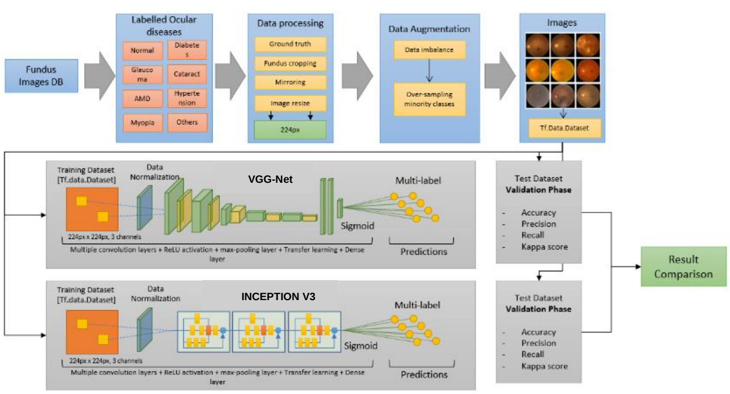


Fig 2. Methodology of Model's Working

4.1 Phase One: Data Acquisition and Inspection

4.1.1. Data Collection: Download the Kaggle ODIR Challenge 2019 dataset.

4.1.2. Initial Data Inspection: Load and inspect the dataset and Perform basic data cleaning.

4.2 Phase Two: Data Preprocessing

4.2.1. Data Splitting: Split the dataset into training, validation, and test sets.

4.2.2. Label Verification: Confirm accurate labeling of ocular diseases. Validate labels against provided ground truth.

4.3 Phase Three: Data Augmentation and Image Processing

4.3.1. Oversampling and Augmentation: Handle data imbalance through oversampling for classed with minority labels. Apply augmentation techniques (rotation, flipping, zooming).

4.3.2. Image Processing: Crop fundus images for relevant regions. Resize images to a consistent 224x224 pixel size. Normalize pixel values.

4.4 Phase Four: Dataset Preparation

4.4.1. Dataset Conversion: Convert processed images into `tf.data.Dataset` format. Split the dataset into batches.

4.5 Phase Five: Model Implementation and Training

4.5.1 InceptionV3 Model :

I) Model Implementation: Implement the InceptionV3 model using TensorFlow or PyTorch. Compile the model with appropriate settings. The following settings were used in this program:-
Loss function = binary_crossentropy
Optimixzer = sgd

II) Training: Train the InceptionV3 model on the training dataset. Monitor training metrics such as loss and accuracy.

4.5.2 VGG-16 Model:

I) Model Implementation: Implement the VGG-16 model using TensorFlow or PyTorch. Compile the model with appropriate settings. The following settings were used in this program:-
Loss function = binary_crossentropy
Optimixzer = sgd

II) Training : Train the VGG-16 model on the training dataset. Monitor training metrics such as loss and accuracy.

4.5.3 EfficientNet B0:

I) Feature Extraction: This model was used for feature extraction, leveraging its learned features for classifying retinal fundus images. EfficientNet B0 is known for its efficiency and effectiveness in image recognition tasks, making it a suitable choice for feature extraction in this project.

II)Adaptive Features: EfficientNet B0 was also employed for feature extraction, capitalizing on its ability to capture complex features in images through its efficient neural network architecture.

III)Task-Specific Tuning: The model was fine-tuned to suit the requirements of the retinal image classification task, ensuring optimal performance in identifying early-stage eye diseases.

Training Details	Inception V3	VGG - 16	Efficientnet B0
Data Augmentation	Yes	Yes	Yes
Transfer Learning	Yes	Yes	Yes
Weights	Pre-trained on ImageNet	Pre-trained on ImageNet	Pre-trained on ImageNet
Last Layer	Global Average Pooling 2D Dense	Dense (8, activation = 'sigmoid')	Global Average Pooling 2D, Dense
Feature Extraction Enabled	Yes	Yes	Yes
Classification Enabled	Yes	Yes	Yes
Optimizer	SGD lr = 0.01, decay = 1e-6, momentum = 0.9, Nesterov = True	SGD lr = 0.001, decay = 1e-6, momentum = 0.9, nestrov = True	SGD, Adam, RMSprop lr = 0.001, decay = 1e-6, momentum = 0.9, nestrov = True
Early Stopping Patience	8 Steps for validation loss, type[min]	8 Steps for validation loss, type [min]	8 Steps for Validation loss, type [min]
Number of Parameters	23, 909,160	134,293,320	5.3 million
Number of trainable parameters	23,874,728	32,776	5.3 million

4.6. Phase Six: Validation and Testing

4.6.1 Validation Evaluation: Evaluate models on the validation dataset. Calculate precision, recall, and kappa score for each class.

4.6.2 Test Evaluation: Assess models on the test dataset. Compute precision, recall, and kappa score.

4.7. Phase Seven : Result Comparison and Analysis

4.7.1. Performance Comparison: Compare performance metrics of InceptionV3 and VGG-16. Analyze differences in accuracy and other relevant metrics.

4.7.2. Visualization: Used confusion metric to compare the output of two models.

5. RESULTS

5.1 Model Training and Performance:

5.1.1 Training Details:

Through extensive experimentation with the introduced models, optimal configurations for each model were identified.

For the Inception model, data augmentation was applied, and the model was initialized with ImageNet weights for transfer learning. Both feature extraction and sorting components were enabled, incorporating a dense layer with Sigmoid activation for the last layer to compute the loss for each of the 8 classes in the output. Stochastic Gradient Descent with a learning rate of 0.01 and binary cross-entropy for the multi-tag configuration were employed. A patience feature was added to halt training if validation loss failed to decrease for 8 iterations. The model comprises 23 million trainable parameters.

In the VGG model, transfer learning with ImageNet weights proved superior to training from scratch. Only the classifier component was enabled, and the last layer was modified for the multi-label problem. The configuration closely mirrors the Inception model, with a reduced learning rate of 0.001 and 32 thousand trainable parameters.

5.1.2 Performance Metrics:

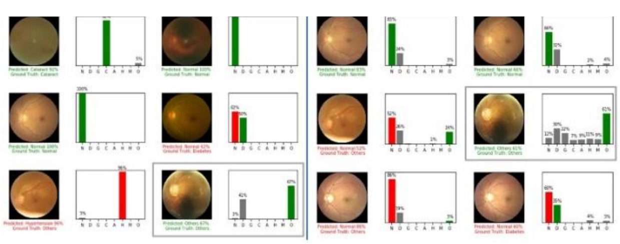
Evaluation of the models demonstrated that the Inception model outperforms the VGG model, achieving 60% accuracy and 55% recall. The final score, considering the mean value of the Kappa coefficient of Cohen, F1-Score, and AUC, is 76%.

While the VGG model exhibits commendable performance, with 57% accuracy, its recall is lower at 36%, indicating that only 36% of the predictions align with the total number of positive images.

5.1.3 Grad CAM Visualizations:

Visualizations using Grad-CAM were presented to highlight regions of interest in medical images.

Table 1. Comparison Between Two Models



7. CONCLUSIONS

In conclusion, the Eye Disease Recognition System, employing deep learning models, represents a significant

Fig 4 Visualization of Results of the Models

been rigorously validated in clinical settings. Its adaptability, e

Fig 4. Visualizational Results of the Models

y integrable into healthcare workflows. By synergizing technology and healthcare, this system contributes to improved early diagnosis, treatment efficacy, and enhanced patient outcomes, establishing new benchmarks in the field of eye disease recognition.

8. REFERENCES

[1] Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G.S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., and, … (2016). Tensorflow: Large-scale machine learning on heterogeneous distributed systems. arXiv preprint arXiv:1603.04467.

[2] Lee, M. Seattle, P. Taylor, U. Kingdom. Machine learning has arrived! Ophthalmology. (2017), pp. 1726-1728.

[3] Bengio, Y., Courville, A. and Vincent, P. (2013). Representation Learning: A Review and New Perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), pp.1798-1828.

[4] Bonet, E. (2018). Què és un fons d'ull? Servei d'Oftalmologia. Fundació Hospital de nens de Barcelona, p.1.

[5] Carletta, Jean. (1996) Assessing agreement on classification tasks: The kappa statistic. Computational Linguistics, 22(2), pp. 249–254

[6] C.I. Sánchez, M. Niemeijer, I. Išgum, A.V. Dumitrescu, M.S.A. Suttorp-Schulten, M.D. Abràmoff and B. van Ginneken. "Contextual computer-aided detection: Improving bright lesion detection in retinal images and coronary calcification identification in CT scans", Medical Image Analysis 2012;16(1):50-62

[7] C.I. Sánchez, M. Niemeijer, A.V. Dumitrescu, M.S.A. Suttorp-Schulten, M.D. Abràmoff and B. van Ginneken. "Evaluation of a Computer-Aided Diagnosis system for

Diabetic Retinopathy screening on public data", Investigative Ophthalmology and Visual Science 2011;52:4866-4871.

[8] Fawcett, Tom (2006) "An Introduction to ROC Analysis"(PDF). Pattern Recognition Letters. 27 (8): 861–874.

[9] García, B., De Juana, P., Hidalgo, F and Bermejo, T. (2010). Oftalmología. Farmacia hospitalaria Tomo II. Publicado por la SEFH. Capítulo 15.

[10] Garrido, R. (2011). Epidemiología descriptiva del estado refractiva en estudiantes universitarios. Universidad Complutense de Madrid, p.339.

[11] Gilbert, C., Foster A. (2001). Childhood blindness in the context of VISION 2020 – the right sight. Bull World Health Organ, 79(3):227-32.

[12] Hijazi, S., Kumar, R. Rowen, C. Using Convolutional Neural Networks for Image Recognition. 2015. Cadence.

[13] Jaworek-Korjakowska, J., Kleczek, P., Gorgon, M. Melanoma Thickness Prediction Based on Convolutional Neural Network With VGG-19 Model Transfer Learning. (2019) The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops.

[14] Kent, Allen; Berry, Madeline M.; Luehrs, Jr., Fred U.; Perry, J.W. (1955). "Machine literature searching VIII. Operational criteria for designing information retrieval systems". American Documentation. 6 (2): 93. doi:10.1002/asi.5090060209. arXiv preprint arXiv: 1409.4842

[15] Krizhevsky, A., Sutskever, I. and Hinton, G. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), pp.84-90.

[16] Kusumoto D, Yuasa S. The application of convolutional neural network to stem cell biology. Inflamm Regen. 2019 39:14. Published 2019 Jul 5. doi:10.1186/s41232-019-0103-3.

[17] Lecun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436–444.

[18] Lyana N. M., & Norshahrizan, N., (2015). The Self-Driving Car.

[19] M.D. Abramoff, Y. Lou, A. Erginay, et al. Improved automated setection of diabetic retinopathy on a publicly available dataset through integration of deep learning Invest Ophthalmol Vis Sci. (2016), pp. 5200-5206

[20] Ocular Disease Intelligent Recognition. (2019). ODIR-2019 - Grand Challenge. [online] Available at: https://odir2019.grand-challenge.org/introduction/ [Accessed 27 Sep. 2019].

[21] Oftalmològica. (2019). Tecnologia per a la revisió de la retina - Àrea Oftalmològica Avançada.

[22] Parampal S. Grewal, Faraz Oloumi, Uriel Rubin, Matthew T.S. Tennant, Deep learning in ophthalmology: a review, Canadian Journal of Ophthalmology, Volume 53, Issue 4, 2018, Pages 309-313, ISSN 0008-4182,

[23] Roletschek, R., (2019). [image] Available at: Fahrradtechnik auf fahrradmonteur.de [FAL or GFDL 1.2 license] [Accessed 3 Nov. 2019].

[24] Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. and Fei-Fei, L. (2015). ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision, 115(3), pp.211-252.

[25] Saine, P. and Tyler, M. (2002). Ophthalmic photography. Boston [Mass.]: Butterworth-Heinemann.

[26] Sermanet, Pierre, David Eigen, Xiang Zhang, Michael Mathieu, Rob Fergus, and Yann LeCun. OverFeat: Integrated Recognition, Localization and Detection Using Convolutional Networks. arXiv:1312.6229 [Cs], December, 2013.