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Research Article

Ocular Disease Recognition System using ResNet50 and InceptionV3 over DenseNet, Xception, VGG and U-Net Architectures

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ABSTRACT

Millions of people worldwide continue to face pre- ventable visual deficit problems arising from undiagnosed eye diseases like diabetic retinopathy, glaucoma, and cataracts. The situation on the ground is even more abysmal in rural areas. The project introduces an Al-based Ocular Detection System, which acts as a sophisticated machine to bridge this gap in healthcare by streamlining the detection of common ocular diseases from retinal fundus images. Using deep learning neural networks in addition to ensemble methods, the system looks forward to increasing the diagnostic accuracy by cutting down the diagnosis time in stress-challenged areas while ensuring improved access to care for the most underserved populations. Automating the image analysis from the retina's perspective by improving the very foundation of rural healthcare enables early diagnosis and, hence, improve vision health outcomes for the patients. The system makes use of the effectiveness of two deep learning models, InceptionV3 and ResNet50, which are well-known for their strong feature extraction capabilities and high accuracy in medical image analysis. These models maintain computational efficiency appropriate for real-time deployment while enabling accurate multi-disease detection from retinal fundus images.

Keywords: Ocular Detection System, Eye Disease Detection, Retinal Fundus Images, Ensemble Learning, ResNet 50, Inception V3, DensNet, UNet, MobileNet, Xception

INTRODUCTION

India's rural population faces significant challenges in accessing healthcare, particularly for eye diseases, which are a leading cause of non-fatal disability. Millions of people suffer from blindness and visual impairment, with rural areas dispro- portionately impacted due to limited access and awareness. In order to solve these problems, our project introduces an innovative expert system that recognizes eye diseases, utilizing a convolutional neural network (CNN) model to facilitate timely diagnosis and reduce vision loss [5]. The goal of this project is to create a reliable and efficient diagnostic tool, with high accuracy, sensitivity, and specificity, especially for underserved rural areas. Beyond developing CNN models, our contributions include advances in image enhancement and segmentation, and a custom CNN trained on processed retinal images to better detect early symptoms of eye diseases. This project has the potential to significantly improve access to accurate and timely eye disease diagnosis, especially in regions with limited healthcare resources.

OBJECTIVES

Limited access to specialized ophthalmic care in rural and underserved areas. High prevalence of preventable blindness due to delayed diagnosis and treatment. Lack of adequate tools for multi-disease classification and real-time analysis. Inadequate user-friendly diagnostic systems for healthcare professionals and patients. Rural and undeserved communities lack access to trained ophthalmologists and diagnostic technology, reducing

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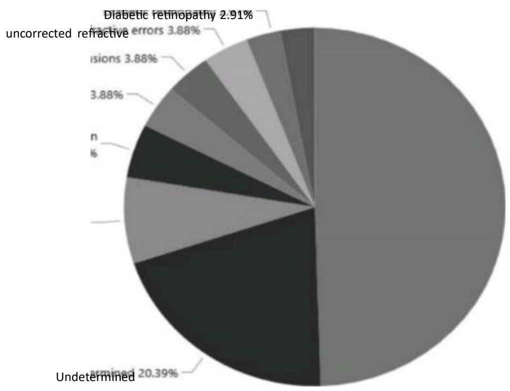
access to early treatment. The high prevalence of ocular diseases such as diabetic retinopathy, glaucoma, and cataracts often leads to a late-stage diagnosis and irreversible vision loss. Existing systems primarily focus on single disease detection, lack scalability, and are resource intensive, making them unsuitable for deployment in low-resource settings [14]. Today?s diagnostic equipment tends to be aimed at experts, leaving general practitioners and healthcare workers with no easy-to-use alternatives. The Eye Disease Recognition System (EDRS) overcomes these challenges using deep learning and human-centered design to offer a reliable, multidisease detection system. It seeks to close healthcare disparities, especially in low-resource settings, through scalable, efficient and accessible diagnostic technolcw.

METHODS

The approach for the Eye Disease Recognition System (EDRS) is explained stepwise so that it is clear and reproducible. The procedure is developed to solve the main issues in ocular disease diagnosis with a speedy and precise deep learning-based methodology.



Corneal occlusions 3.88%

Chddhood 388%

Age-related macular degeneration

4.85%

— cataract 49.51%

Glaucoma 7.77%

Fig 1. Literature on Blockchain Adoption in Tourism

Components of eye disease recognition system

Labelled ocular disease	Data preprocessing	Data Augmentation	Images	Training Dataset	Testing dataset
• Normal • Diabetes • Glaucoma • Cataract • AMD • Hypertension • Myopia • Other	• Ground Truth • fundus cropping • mirroring • image resize : 224 pixel.	• Data imbalance: over sampling minority classes	dataset	• resnet 18 • inception V3	• Validation phase • Accuracy • precision • Recall

Fig. 2. Components of eye disease recognition system

Dataset Sources: Retinal fundus images were obtained from public datasets such as EyePACS and IDRiD.Dataset Properties: EyePACS: Contains images annotated for diabetic retinopathy severity. IDRiD: Offers annotated images

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for both diabetic retinopathy and other retinal disorders [4]. Image Resizing: All the images were resized to 224x224 pixels to satisfy the input needs of CNN architectures. Normalization: Pixel values were normalized to between 0 and 1 for con- sistent input distributions and facilitating convergence while training. Data Augmentation: Horizontal flip, random rotation, and oversampling of minority classes were implemented to increase dataset diversity and avoid overfitting. Techniques like resizing, normalization, and augmentation were performed following TensorFlow standards [7].

ResNet50: Selected for its residual learning structure, which prevents vanishing gradients and enables deep feature extrac- tion. InceptionV3: Chosen for its capacity to extract multi- scale features, which makes it suitable for intricate retinal structures. Transfer Learning: Both models were pre-trained with ImageNet weights, which saved training time and en- hanced performance on medical image datasets [2].

Training Process: The images were split into training (70 Percent), validation (20 Percent), and testing (10

Percent) sets. The models were trained with a cross-entropy loss function and an adaptive learning rate optimizer

(e.g., Adam). Early stopping was used to avoid overfitting by tracking validation performance [7]. Hyperparameter Tuning: Hyperparameters like learning rate, batch size, and number of epochs were tuned to obtain maximum model performance. Cross-Validation: K- fold cross-validation was used to assess model stability on various subsets of the data.

Performance Measures:Accuracy, precision, recall, Fl- score, and area under the curve (AUC) were employed to evaluate model performance[1][5]of classifyingof classifyi. Confusion matrices were examined to determine where there was misclassification and to enhance diagnostic sensitivity.

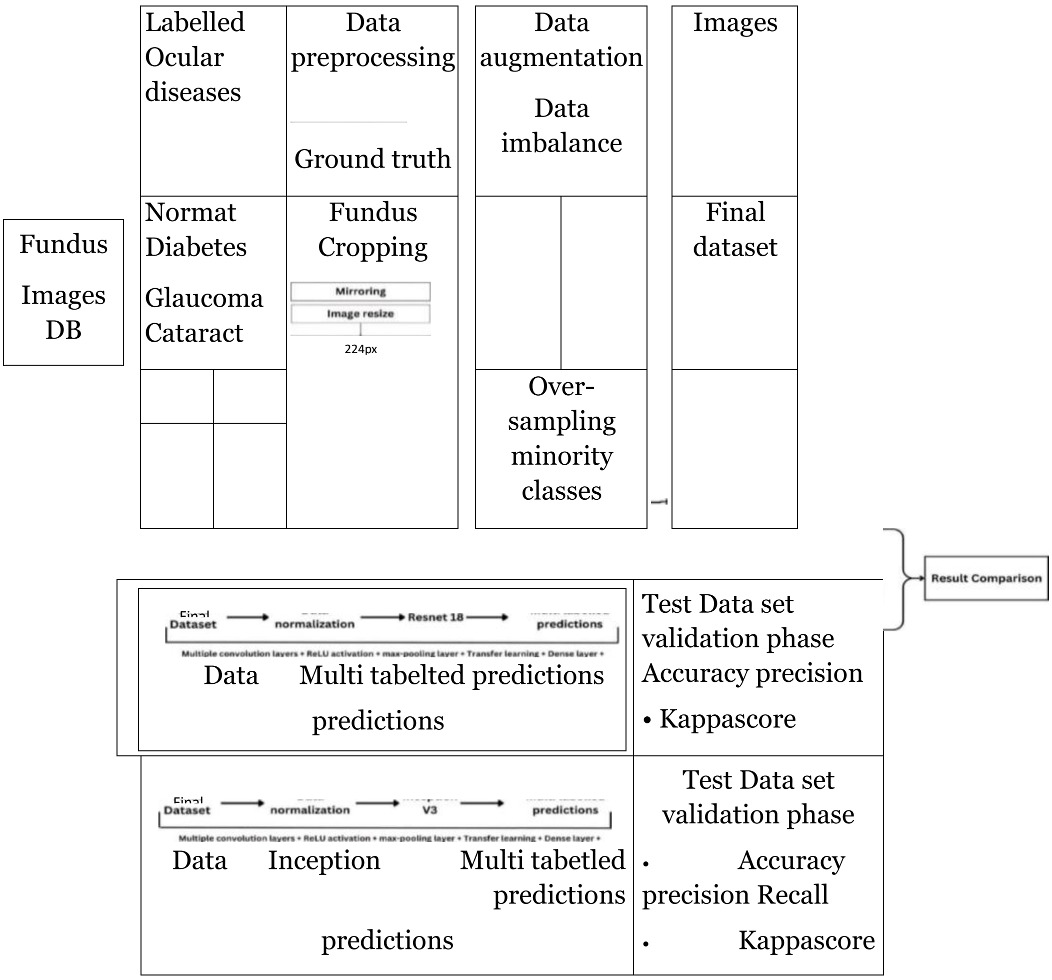

Fig. 3. System Architecture

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Key Features:lmage Upload: It is the ability to upload retinal images for anal- ysis.Visualization: This includes heatmaps and classification probabilities.

To guarantee high accuracy and dependability, the system architecture for the ocular disease recognition system is planned in a methodical and modular fashion. A publicly accessible database is used to gather retinal fundus images, and each image is labeled with the corresponding ocular diseases, including diabetic retinopathy, glaucoma, cataract, hyperten- sion, age-related macular degeneration (AMD), myopia, and others. Confirming the ground truth labels, cropping the fundus region to focus on the area of interest, applying mirroring for augmentation, and uniformly resizing the images to 224 x 224 pixels are some of the crucial steps that are included in the data processing phase that follows data acquisition. These procedures guarantee that the input data is standardized, clean, and appropriate for deep learning model feeding.

Data augmentation techniques, particularly oversampling minority classes to ensure balanced learning, are used to address class imbalance in the dataset and improve model performance even further. To enable effective training, the preprocessed and enhanced photos are subsequently formatted into a TensorFlow dataset pipeline. A transfer learning tech- nique is used to apply two potent convolutional neural network (CNN) models, ResNet50 and InceptionV3, where pre-trained weights on ImageNet are adjusted to fit the particular task of classifying ocular diseases [1] [2]. Both models include multiple convolution layers followed by ReLU activation, maxpooling operations, and a dense output layer with sigmoid activation to perform multi-label classification, allowing the system to detect the presence of one or more diseases in a single image.

Key performance metrics like accuracy, precision, recall, and the Kappa score are used to assess the models during the validation phase following training. These metrics offer a thorough comprehension of the efficacy of every model. In order to determine which model provides the best overall performance in terms of predictive accuracy and generaliza- tion, the outcomes from ResNet50 and InceptionV3 are finally compared. This design guarantees a comprehensive automated system that can accurately identify various eye conditions early on, facilitating better clinical decision-making, particularly in healthcare settings with limited resources. We thoroughly examined a number of deep learning architectures frequently employed in medical imaging as part of our strategy to develop an effective and precise ocular disease recognition system. We chose InceptionV3 and ResNet50 as the primary models for classification following extensive testing and a review of recent research. Since its inception modules employ parallel filters of different sizes (IXI, 3x3, 5x5), InceptionV3 was selected for its capacity to capture multi-scale features [2]. It can effectively analyze intricate retinal patterns and textures thanks to this architectural advantage, particularly in high-resolution fundus images. Because ResNet50 uses residual connections, which enable the model to go deeper without experiencing vanishing gradients [1], it was chosen. This improves its ability to identify visually similar eye diseases by extracting deep hierarchical features from images.

Since both models have already been trained on ImageNet, transfer learning can be effectively used on medical datasets with shorter training times and better convergence.

Why Not Use Different Architectures?

Xception: Xception is computationally more expensive dur- ing training and did not produce noticeably better results in early trials with our dataset, despite using depthwise sep- arable convolutions for efficiency. Additionally, it demon- strated increased susceptibility to hyperparameter adjustment. DenseNet: Because feature maps are concatenated across all layers, DenseNet-121 and its variations were found to be slower to train and more memory-intensive, despite their encouraging results in the literature [8]. ResNet50 was chosen because of our limited resources and the requirement for quicker experimentation [8].

VGG16/VGG19: These models are more in-depth, but their architecture is less effective. In our situation, they don't pro- vide appreciable performance gains over ResNet or Inception, but they do demand more parameters and processing power. On smaller datasets, VGG also has a tendency to overfit [9]. UNet: Primarily a segmentation model, UNet works well for tasks requiring pixel-by-pixel labeling, such as blood vessel segmentation. UNet wasn't appropriate for our main objective because our task is image classification.

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MobileNet: With a slightly reduced accuracy, MobileNet's speed and lightweight architecture make it ideal for mobile and edge deployment. For this research phase, we focused on classification performance, even though it is perfect for deployment in environments with limited resources.

In conclusion, InceptionV3 and ResNet50 were chosen due to their ability to balance architectural robustness, training ef ficiency, and accuracy. In our evaluation, they performed better than other models while still being useful for actual medical applications, particularly in diagnostic support systems where dependability is crucial.

RESULTS

Training details: Inception v3 has a lot more trainable parameters, which suggests that more layers were optimized [1]. There are fewer trainable parameters because ResNet50 was primarily used in a frozen state for feature extraction [2]. For multi-label classification and early stopping to prevent overfitting, both models employed binary cross-entropy.For performance optimization, various dense layer configurations and learning rates were investigated. Model comparison: Inception V3 Model Accuracy and Loss Plot Description: This figure shows the accuracy and loss curves of the Inception V3 model for training and validation. It illustrates the model's learning trajectory across epochs. Proper convergence and successful learning are indicated by a steady increase in validation accuracy and a concurrent drop in loss.

Training Detail	Inception v3	Resnet 18
Data Augmentation	yes	yes
transfer learning	yes	yes
Weights	Pre-trained on ImageNet	Pre-trained on ImageNet
feature extraction enaabled	Yes	No
Optimizer	SGD Ir--0.01, decay=1e-6, momentum=O.9, nesterov-- True	SGD Ir=O.OOI, decay=1e-6, momentum-0.9, nesterov= True
classification enabled	yes	yes
Loss function	Binary Cross-Entropy	Binary Cross-Entropy
Early stopping patience	8 steps for validation loss, type [min]	8 steps for validation loss, type [min]
Number of parameters	23,909,160	134,293,320
number of trainable parameters	23,874,728	32,776

Fig. 4. Training Details

Key Takeaway: Due to its deeper and wider architecture, Inception V3 demonstrated strong generalization ability, stable training behavior, and reduced overfitting.

ResNet50 Model Accuracy and Loss Plot Description: This plot displays the accuracy and loss of the training and validation of the ResNet50 model. The steady increase in accuracy and decrease in loss suggest that ResNet50's residual connections improved model depth utility and assisted in resolving vanishing gradient issues.

Key Takeaway: ResNet50 demonstrated reliable perfor- mance throughout the training, demonstrating how well skipped connections preserve gradient flow.

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MODEL	VAL LOSS	PREDICTION	PRECISION	RECALL		SCORE	F-1 SCORE	AUC VALUE	FINAL SCORE
Inception v3	0.3769	0.8984	0.6021	0.552	0.855	0.5186	0.8984	0.8838	0.7669
Resnet50	0.3137	0.8871.	0.5776	0.3625	0.8140	0.3863	0.8871	0.8176	0.6970

Fig. 5. Model Comparison

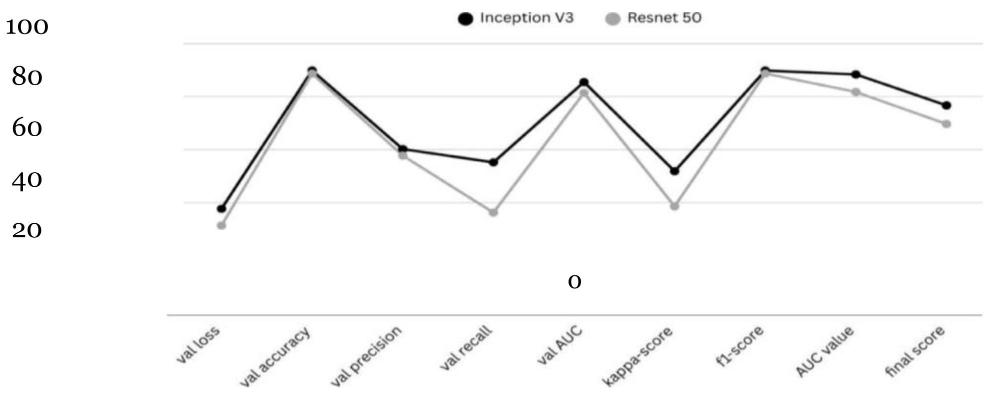

Fig. 6. Model Comparison graph

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