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# DIAGNOSING OF EYE RELATED DISEASE USING DEEP LEARNING ALGORITHM

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**ABSTRACT:**

According to the World Health Organization, visual impairment is a global health issue, with billions of cases preventable through regular eye tests. In emerging and developing countries, a lack of specialists inhibits accurate diagnosis of eye diseases and increases blindness count. This paper introduces a convolutional neural network (CNN) ensemble using transfer learning to diagnose eye diseases. The training involved high-quality fundus images, with testing on low-quality images from the minimum equipment cost. Despite lower image quality, the system demonstrated high accuracy in detecting various eye-related diseases, displaying the efficiency of deep learning techniques. These results highlight the potential of such approaches to improve eye disease diagnosis, especially in under-resourced healthcare systems.

**Index terms**: Convolution Neural Network, Transfer learning, Eye disease, Fundus image.

## INTRODUCTION

The increasing global life expectancy has contributed to a rise in eye complications, with many blindness-related diseases being asymptomatic. According to the World Health Organization (WHO), a significant number of vision impairment cases could be prevented with regular eye examinations and proper treatment. This issue is particularly prominent in emerging and underdeveloped countries, where preventable blindness disproportionately affects low-income populations. In this context, Clinical Decision Support (CDS) systems, particularly those utilizing machine learning algorithms like convolutional neural networks (CNNs), present a promising approach to enhancing diagnostic accuracy by providing clinicians with evidence-based insights.

This paper proposes a CNN-based ensemble method for classifying eye conditions. The approach employs transfer learning with pre-trained models to identify common eye conditions, including cataracts, diabetic retinopathy, age related macular disease and glaucoma. One of the key advantages of the proposed method is its ability to maintain high diagnostic accuracy even when working with low-quality images, commonly found in resource-constrained settings. By leveraging transfer learning, the model can be trained effectively with a smaller dataset, improving the speed and accuracy of diagnosis. The results demonstrate the potential of CNN-based systems to enhance eye disease diagnosis and support early detection, especially in regions with limited access to specialized healthcare

## LITERATURE REVIEW

Research on applying machine learning algorithms to recognize eye-related disorders from photographs has gained significant attention throughout the last ten years. The techniques that advance the state of the art are then discussed chronologically, with a focus on those that take these problems into account.

### *CATARACTS*

To extract features, a transfer learning technique using a pre-trained CNN was taken into consideration. An SVM conducts cataract classification in the sequence. Ophthalmologists assisted in the labelling work, and the authors used publicly available datasets. Nevertheless, a detailed explanation of this data curation method was lacking. The suggested method achieved an average accuracy of 92.9% [2]. A dataset of fundus pictures was used to identify cataracts using a unique deep learning model called Cataract Net. This model generates the best results in the literature with accuracies of over 98%. It is crucial to note, nevertheless, that even though the authors do a comparative study, the data are not identical; therefore, it cannot be deemed sufficient. Given the requirement for a publicly available dataset that has been well curated, it is important to note that setting a baseline for cataract diagnosis and classification is not an easy undertaking. Nevertheless, it is anticipated that predictive models would be able to attain accuracy levels higher than 90%.

### *DIABETIC RETINOPATHY*

Diabetic retinopathy (DR) is a diabetes complication that damages retinal blood vessels, potentially leading to vision loss. Early detection of referable DR is crucial for implementing preventive measures. Naïve Bayes achieved 83.4% accuracy compared to 64.9% for SVM on a limited dataset of 300 images [4]. Inception-v3 CNNs trained on EyePACS and Indian hospital data achieved sensitivity between 96.1%-98.5% and specificity between 87.0%-93.9% on curated datasets. Multiethnic population data of 497,821 images resulted in 91.5% sensitivity and 90.6% specificity.

Adaptive visualization tools using deep learning achieved 96% true positives, while ensemble models with ResNet50, Inception-v3, and others attained an accuracy of 80.8% but had variable recall and F1-scores [3]. InceptionResNet-v2 models further improved sensitivity for both pathological and healthy retinas, reaching 80% and 98%, respectively. Challenges in comparing studies arise due to varying datasets, metrics, and data curation, emphasizing the need for standardized evaluation methods.

### *AGE RELATED MACULAR DISEASE*

One of the main causes of visual impairment in those over 50 is age-related macular degeneration (AMD), which affects the macula. It is divided into two categories: wet (exudative) and dry (non-exudative). To avoid serious vision impairment, early identification is crucial.
Sensitivity and specificity have surpassed 90% for deep learning models, especially CNNs like Inception-v3, which have been trained on big datasets. With accuracies above 80%, ensemble models that combine architectures like ResNet and DenseNet also exhibit potential. While preprocessing methods like Gaussian filtering increase model sensitivity for AMD phases, visualization tools improve interpretability. Variability in datasets, assessment criteria, and curation procedures are among the difficulties, highlighting the necessity of defined standards to guarantee reliable AMD detection and classification results.

### *GLAUCOMA*

Colour fundus photos, patient ages, and diagnostic keywords are all included in the publicly accessible Ocular Disease Intelligent Recognition (ODIR) dataset. The dataset includes fundus photos of 5,000 patients from different Chinese medical facilities, including pictures of the left and right eyes. The Kowa, Canon, and Zeiss camera systems used to take these pictures produced a range of image resolutions.

A subset of the dataset was used for glaucoma detection, using a balanced picture distribution to guarantee objective predictions. Normal, glaucoma, and cataract eye images were equally represented in the data, which was divided into 80% training (4,000 photos) and 20% testing (1,000 images). Cross-validation methods, such as leave-one-out cross-validation and randomized data partitioning, were used to reduce the hazards of data leaking and overfitting. By reducing the likelihood of overfitting or underfitting and ensuring strong training, these techniques increased the model's dependability for glaucoma detection.

## PROPOSED SYSTEM

To develop an advanced eye complaint individual tool, the system will work pretrained Convolutional Neural Networks (CNNs), which will be fine-tuned using high-quality retinal images to ameliorate the bracket of eye conditions similar as glaucoma, cataracts, diabetic retinopathy, and macular degeneration. These models, originally trained on large, different datasets, will be customized to fête the specific nuances in retinal images, icing high delicacy in opinion. The processing of these images and the individual calculations will be hosted moreover on a pall platform or an original garçon, enabling real-time results.

In addition to the individual features, a web-grounded case gate will be developed using framework like Angular or React to offer substantiated eye health information to users. This gate will display individual results, suggest treatments, and give ongoing eye care recommendations. The gate will also integrate drive announcements to remind cases about follow-up movables, medication schedules, or life changes, icing nonstop monitoring and engagement. To further enhance case well-being, the system will incorporate an internal health point, offering resources similar as stress-relief ways, relaxation exercises, and access to internal health professionals. as the emotional impact of eye conditions can frequently affect overall health. To ensure flawless functionality, the system will use secure databases and APIs for data synchronization and operation of case records, maintaining the sequestration and security of sensitive medical information. Regular testing on real-world data will be performed to insure the delicacy of judgments, usability of the platform, and compliance with data security norms similar as HIPAA or GDPR. This will ensure the tool's trustability, making it a stoner-friendly and effective individual system for cases and healthcare professionals likewise.

## IMPLEMENTATION

### *DATA HANDLING AND PREPROCESSING*

The high-quality images used to retrain the CNNs VGG16 were obtained from a publicly available dataset on Kaggle, specifically curated for the diagnosis of various eye-related diseases. These images represent conditions such as diabetic retinopathy, cataracts, age-related macular degeneration (AMD), and glaucoma. Since the dataset includes images generated using different equipment. and techniques, there are inherent variations in size, aspect ratio, colour, focus, and quality. To ensure consistency, all images were standardized to a resolution of 299 × 299 pixels in the RGB scale, with the ocular fundus cantered and cropped.

To refine the dataset further, a filter was applied to remove mis-captured images that were either predominantly black or white. This was achieved by converting the RGB images to grayscale and calculating the average pixel intensity. Threshold values were defined to identify and eliminate such images, ensuring only high-quality, diagnostically relevant samples of diabetic retinopathy, cataracts, AMD, and glaucoma were retained. The final dataset serves as a robust foundation for training and evaluating deep learning models for the accurate diagnosis of these eye conditions.

***ENSEMBLE MODEL***

Ensemble methods are advanced algorithms that merge multiple machine learning approaches into a single predictive framework. They can be used for different objectives, such as decreasing variance (Bagging), bias (Boosting), or improving predictions (Stacking). Stacking is a technique employed to integrate information from several predictive models in order to create a new, unified model. The stacked approach often outperforms individual models due to its smoothing nature. Stacking highlights the strengths of each base model where it performs best and diminishes its influence where it performs poorly. Therefore, stacking works best when the base models exhibit substantial differences. We used stacking to improve the prediction of our model, as evident from our results. The proposed approach ensembles five deep CNN models: ResNet50, InceptionV3, Xception, Dense121, and Dense169. This Algorithm represents the proposed model in detail.

Let H = {InceptionV3, ResNet50, Dense121, Dense169, Xception} be the set of pre-trained models. Each model is fine-tuned with the Fundus Images dataset (X, Y), where X is the set of N images, each sized 512 × 512, and Y contains the corresponding labels, Y = {Normal, Mild, Moderate, Severe, PDR}.

Here, h (x, w) is the CNN model that predicts classy for input x given w, and l() is the categorical cross-entropy loss penalty function. The Nadam optimizer, which incorporates Nesterov acceleration, is used to fine-tune the learning parameters.:

$$L (w, X_i) = 1/n \ \Sigma \ \{x \in X\_i, y \in Y_i\} \ l (h (x, w), y)$$

Here, h (x, w) is the CNN model that predicts classy for input x given w, and l() is the categorical cross-entropy loss penalty function. The Nadam optimizer, which incorporates Nesterov acceleration, is used to fine-tune the learning parameters:

$$w_{\{t+1\}} = w_t - (\beta / \sqrt{} (\hat{v} + \varepsilon)) (\hat{m}_t / (1 - \beta_1{}^\wedge t)) \ \partial/\partial w_t \ L (w_t, X_i)$$

Here, β, m̂, and v̂ represent the learning rate, the first-order moment, and the second-order moment of the gradient, respectively. Meanwhile, β_1 and β_2 represent the decay rates, initially set to 0.9. The Nesterov method helps determine the direction of the next step and avoids fluctuations. Initially, $w_t$ (t = 0) is set to the learned weights of the model h ∈ H using transfer learning. The output layer of each model, h ∈ H, uses SoftMax as an activation function to generate the probabilities of the input belonging to the different classes {Normal, Mild, Moderate, Severe, PDR}.

The learning rate β starts at 0.01 and is gradually reduced by a factor of 0.1 until it reaches 0.00001. We use 50 epochs for training with early stopping if the model starts overfitting.

During testing, to predict the class label of an unseen example, we use stacking to combine the results of all different models and generate a unified output. The ensemble method leverages the strengths of each individual model, resulting in improved overall performance. Let x test represent a new test sample; the ensemble output is defined as::

$$\hat{m} = arg \ max_m \ \Sigma_{\{h \in H\}} \ h (w, x_{test}) / |H|$$

Here, h () denotes the fine-tuned model, |H| represents the total number of models, and m refers to the different modalities, where m ∈{Normal, Mild, Moderate, Severe, PDR}.. In the case of imbalanced training data, accuracy tends to bias toward majority classes

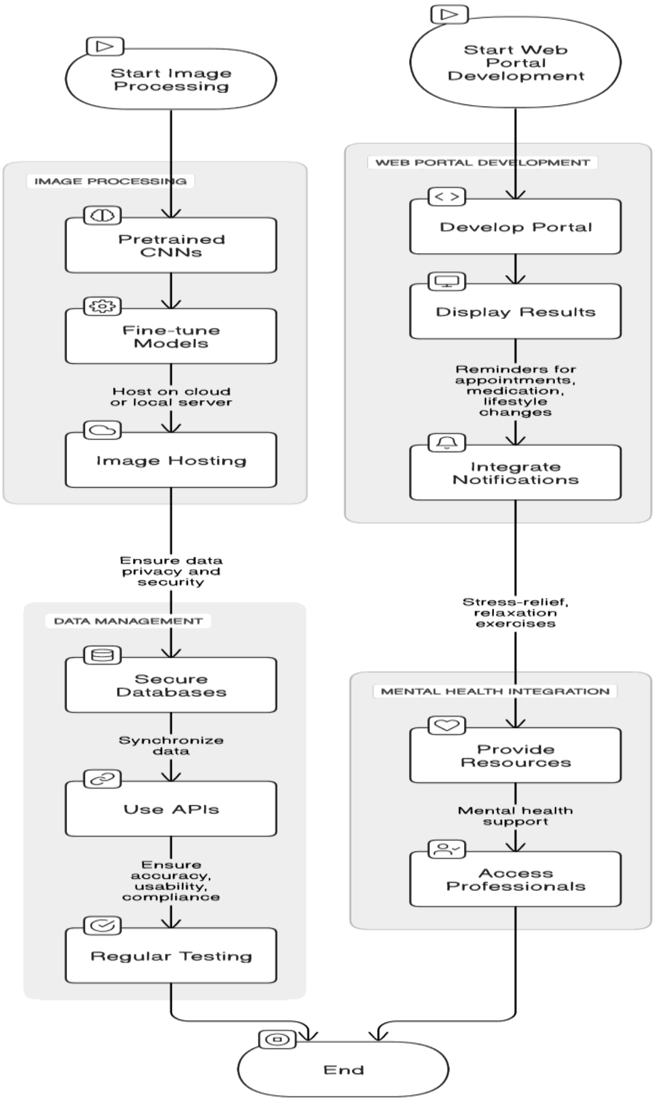



**Fig 1: Block Diagram Representation of Eye Diagnosing**

## RESULTS

The results of the proposed approach are categorized into two sections: (A) Exclusive Dataset and (B) Open Datasets. The proprietary dataset does not allow for direct comparisons due to its exclusive nature, while the public datasets facilitate comparisons with other similar works in the field. In both cases, the models were trained individually for each eye condition. Images of altered retinas were specific to the condition being trained, while images labelled as "normal" were used across all models.

**A. Exclusive Dataset**

For the proprietary dataset, four models were trained for distinct eye conditions using high-quality images. Subsequently, these models were retrained with low-quality images to demonstrate the transfer learning approach. A comparative analysis was conducted by training another set of four models solely on the low-quality dataset.

**B. Open Datasets**

To validate the model's performance on widely available datasets, public datasets commonly used in research literature were employed. These included two datasets for diabetic retinopathy (Messidor-2 and EyePACS), the ODIR dataset for cataract classification, and the REFUGE dataset for glaucoma detection. The use of public datasets is essential for establishing benchmarks and ensuring model credibility. However, many studies preprocess or curate the data, often altering class labels without providing detailed descriptions of these modifications. This lack of transparency makes it challenging to establish consistent benchmarks for predictive models. Nonetheless, the proposed approach was tested against these datasets, demonstrating its effectiveness across various eye conditions.

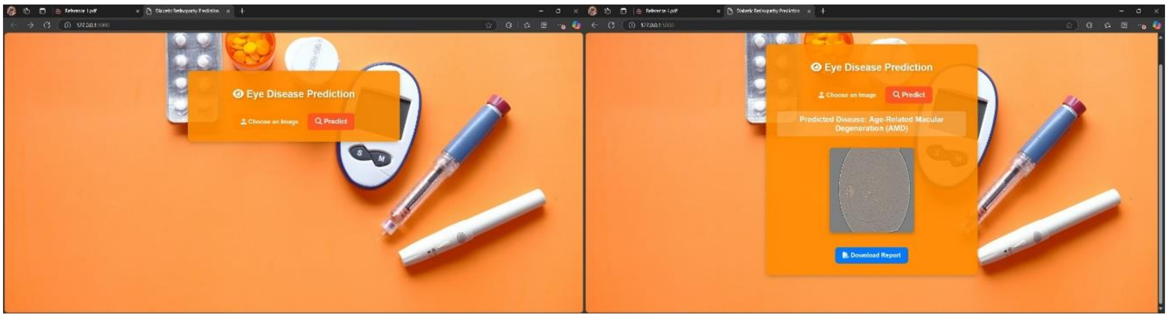
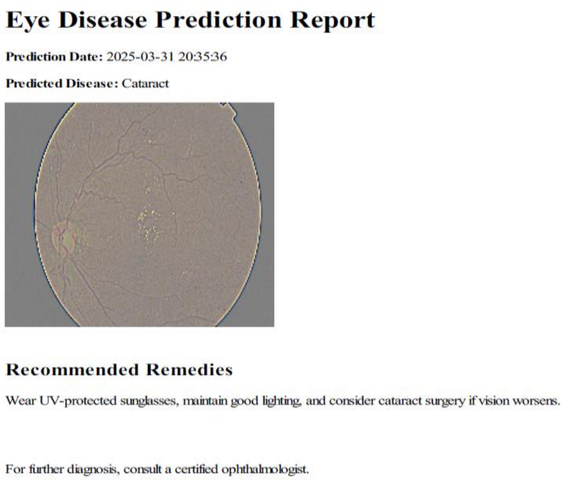



**Fig 2: Image Prediction Interface**



**Eye Disease Prediction Report**

**Prediction Date:** 2025-03-31 20:35:36

**Predicted Disease:** Cataract

**Recommended Remedies**

Wear UV-protected sunglasses, maintain good lighting, and consider cataract surgery if vision worsens.

For further diagnosis, consult a certified ophthalmologist.

**Fig 3: Report of the predicted Eye Disease**

## CONCLUSION

In conclusion, the proposed eye diagnosing system leverages advanced technologies such as pretrained Convolutional Neural Networks (CNNs), IoT integration, and secure data management to deliver an efficient and reliable solution for identifying eye conditions like glaucoma, cataracts, and diabetic retinopathy. The inclusion of a user-friendly web portal ensures seamless access to diagnostic results, treatment suggestions, and follow-up reminders, enhancing patient engagement. Additionally, the integration of mental health resources addresses the emotional impact of eye disorders, promoting holistic well-being. By adhering to data security standards such as HIPAA or GDPR and undergoing regular testing, the system ensures accuracy, privacy, and usability, making it a comprehensive and trustworthy tool for both patients and healthcare providers.

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