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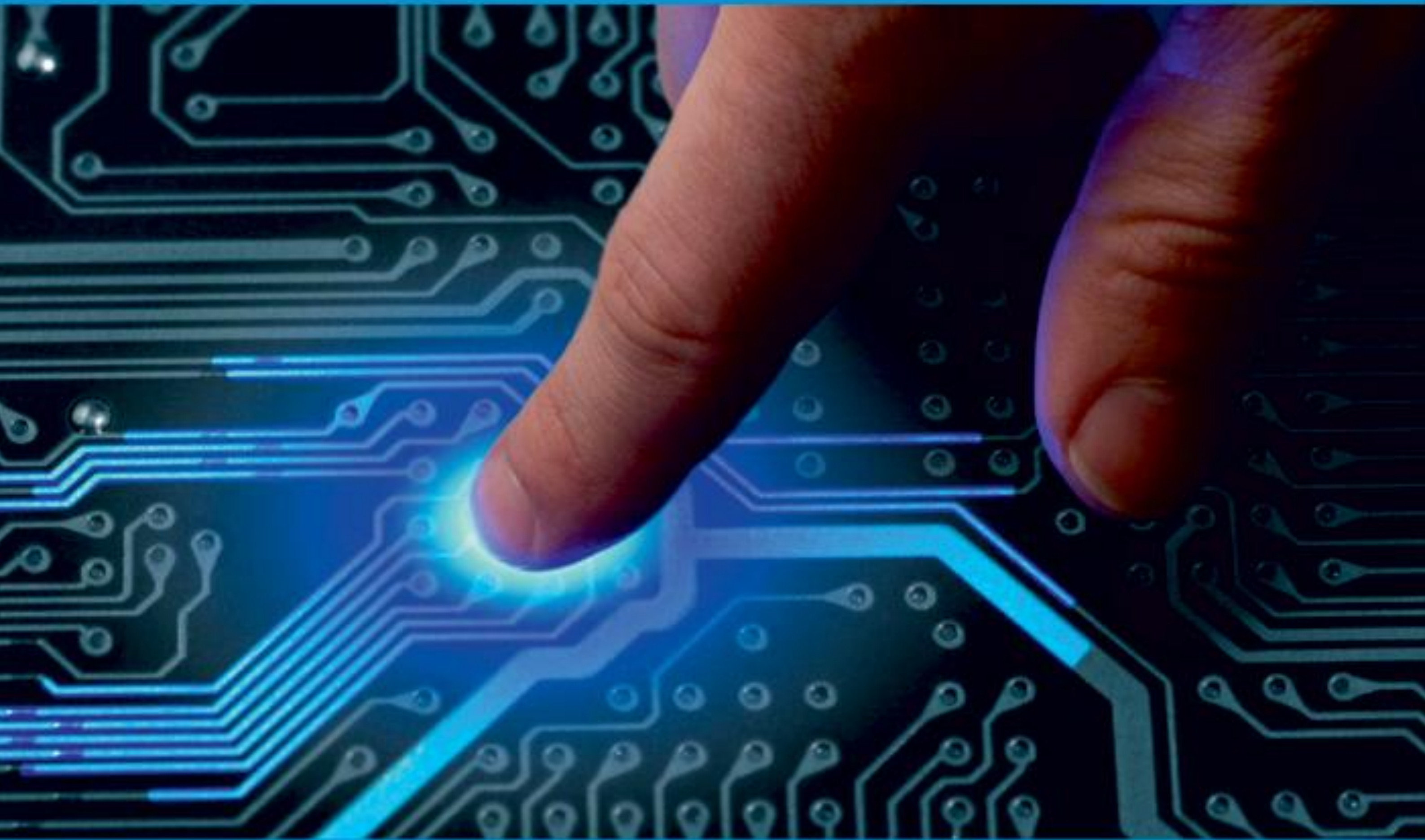

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Automatic Detection of Eye Cataracts Using Convolution Neural Networks (CNNs), Support vector Machine (SVM), and Inception-V3

Raja Sagar, Rohith K V, Suman P, Suhas S, Prof. N. Thanuja

B.E Students, Department of CSE, Bangalore Institute of Technology, Bangalore, India

Assistant Professor, Department of CSE, Bangalore Institute of Technology, Bangalore, India

ABSTRACT: A disease called cataracts causes the lens of the eye to become opaque or cloudy. This is one of the most common causes of blindness and limits vision. Consequently, early detection and prevention of glaucoma can reduce blindness in patients and their postoperative suffering. This study presents a system based on a Convolution Neural Network, Support Vector Machine, and Inception-V3 for glaucoma detection in the eyes. The proposed system can provide accurate results for fundus images, slit-lamp images, and visible wavelength images which are captured using a DSLR camera or mobile camera. Here training a model is done using all three types of images and for three types of models.

KEYWORDS: Cataract; CNN; SVM; InceptionV3:VW(Visible wavelength Images)

I. INTRODUCTION

Cataract is a disease that results from the clouding of one or both lenses of the eye. The main symptom of this eye condition, often associated with aging, is blurred vision. The eyes are mostly water and protein. Cataracts are one of the eye diseases often leading to blindness. According to the Vision 2020 report, glaucoma is responsible for 62.5 million visual impairments and blindness worldwide. This number is expected to increase to 71.5 million by 2022 due to an aging population. Due to inadequate healthcare facilities and a shortage of ophthalmologists, a large proportion of glaucoma patients remain undiagnosed and as a result, glaucoma diagnosis remains a major public health problem. Many factors can cause cataracts, including aging, smoking, radiation, and diabetes. Early diagnosis and treatment of migraine is essential to maximize early benefits, as delay can lead to irreversible blindness making it very difficult to diagnose and assess at the onset of migraine. In rural areas and remote areas, people are most impaired due to a lack of proper health facilities and ophthalmologists. Therefore, For a long time, research has focused on developing intelligent ways to detect cataracts in the eyes. Several technological devices have recently been developed to detect cataracts in fundus images and slit-lamp images. However, the cost of taking these images in a hospital costs more, and detection of cataracts through these images can take a while to examine the images. In Fundus images, the cataract is detected based on the visibility of retinal blood vessels. Whereas, in slit-lamp images, it is detected by a device called slit-lamp which, provides different colors on eyeballs based on the type and intensity of cataracts. The acquisition of these images usually requires a great deal of effort and expertise on the part of qualified professionals. Therefore, there is a need to develop an intelligent computer-assisted glaucoma diagnosis system. Such a system would improve access to eye care by reducing the need for optometrists to perform tasks such as cataract diagnosis. This paper proposed a cataract detection system on the fundus, slit-lamp, and visible wavelength images using CNN, SVM, and Inception-V3.

II. LITERATURE SURVEY

Sl No.	Title	Authors	Year	Contribution and Limitations
1	Identification and Classification of Cataract Stages in Old Age People Using Deep Learning Algorithm.[IEEE]	Sahana M, Gowrishankar S	2019	**Contributions-** Use a deep learning algorithm for the identification and classification of cataract stages in old age people. The algorithm utilizes a convolutional neural network (CNN) for feature extraction and classification of cataract images.

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				Limitations- Limited data availability for old age people ,Ethnic and demographic variability
2	Automatic Detection of Eye Cataract using Deep Convolution Neural Networks [IEEE]	Md.Rajib Hossain, SadiaAfroze, Nazmul Siddique	2020	**Contributions-**Developing an automatic cataract detection system using Deep Convolution Neural Networks (DCNNs) is to train a DCNNs model with labeled data sets of retinal fundus images. The DCNNs model, based on Res-Net50 architecture, is trained to detect cataract and non-cataract images. **Limitations-** Pre-processing overlookedand Image prep unaddressed
3	Unified Diagnosis Framework for Automated Nuclear Cataract Grading Based on Smartphone Slit-Lamp Images.[IEEE]	Iaoting Wang , Hong Wu	2020	**Contributions-**Develop a cataract severity classification algorithm based on deep learning. The algorithm aims to automate the detection and classification of cataracts in the anterior eye using artificial intelligence. The framework integrates three different artificial intelligence networks to improve the accuracy of diagnosis and reduce false positives. **Limitations-** Data Bias and Generalization.
4	Artificial Intelligence for Cataract Detection and Management [IEEE]	Ayesha Anees, Yih-Chung Tham	2020	**Contributions-** Explore AI applications in cataract diagnosis, emphasizing deep learning's accuracy in detecting and grading cataracts. It discusses AI's role in enhancing IOL power calculation, especially in complex cases, stressing the necessity for further research and real-world evaluations. **Limitations-**Challenges with atypical biometric profiles and past refractive surgery
5	CataractNet: An Automated Cataract Detection System Using Deep Learning for Fundus Images.[IEEE]	Masum shah junayed, Md baharul islam, Arezoo sadeghzadeh, and Saimunur rahman.	2021	**Contributions-** Develop a deep learning system called CataractNet for automated cataract detection in fundus images. CataractNet is a Convolutional Neural Network (CNN) that integrates the feature extraction phase and the classification process into a single

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				model. This network is designed to detect cataracts in fundus images. The system consists of three main steps: pre-processing, feature extraction, and classification. **Limitations-** Lack of Grading Precision
6	Cataract Disease Detection by Using Transfer Learning-Based Intelligent Methods[HINDAVI]	Md Kamrul Hasan, Tanjum Tanha	2021	**Contributions-**Employ CNNs, specifically Inception -ResNet V2, for cataract classification using a public dataset. The focus is on transfer learning techniques for early cataract detection and prevention strategies. **Limitations-** Lack of External Validation

III. PROPOSED SYSTEM

In our study, we propose a robust cataract detection system leveraging a combination of convolutional neural networks (CNNs) and a voting scheme to enhance prediction accuracy. Initially, we gathered a diverse dataset comprising normal eye images, fundus eye images, and slit-lamp eye images. We utilized a modified InceptionV3 model to extract high-level features from these images, focusing on the last convolutional layer for feature representation. Subsequently, we trained three separate CNN models on the extracted features, each tailored to the characteristics of the specific image types.

To consolidate the predictions from these individual models, we implemented a simple majority voting scheme. This approach aggregates the predictions from each model and selects the final prediction based on the majority vote. This ensemble technique helps mitigate potential biases or weaknesses inherent in individual models, thereby improving overall prediction robustness.

To facilitate easy access and utilization by clinicians or end-users, we developed a user-friendly interface. This interface allows users to upload eye images effortlessly and receive real-time cataract prediction results. By integrating the ensemble model within an intuitive interface, our system offers a practical solution for early cataract detection, enabling timely intervention and improved patient outcomes.

Our experimental results demonstrate the efficacy of the proposed approach, achieving high accuracy in cataract prediction tasks. Furthermore, the user-friendly interface ensures accessibility and usability, enhancing its potential for widespread clinical adoption. Overall, our study presents a novel framework combining deep learning techniques with ensemble methods, offering a promising avenue for efficient and accurate cataract diagnosis in clinical settings.

IV. MEHOODLOGY AND APPROACH

This study presents a method for mild and medium cataract detection based on training and testing modules using the CNN, SVM, and Inception-V3 classification methods. Labeled data sets are used in the training module to train the system. The test module then examines the unlabeled data. The dataset is divided into 80 percent for training and 20 percent for testing in each of the image types.

a. Training module

In this paper, there are three different training modules and each training module has its corresponding testing module. Let us start with the training module with the CNN algorithm. In the CNN algorithm, TensorFlow uses the ImageDataGenerator class to configure data generators and prepare images for training. To improve model training and to ensure accuracy, resize image data to normalize pixel values from 0 to 1. During training, images are created with them using the flow_from_directory method matching characters This method quickly and easily imports images from specified directories. These features help to efficiently prepare and organize data for deep learning model training, and improve model accuracy and efficiency. The neural network is constructed using a series of models, and layers are

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assembled one at a time. Several Conv2D layers and MaxPooling2D layers make up the model architecture, making it easy to extract important features from the input image by performing convolution and pooling operations and then flattening the feature maps into one-dimensional arrays using Flatten layers. The ReLU processing function is used in the convolutional layer to support feature extraction by introducing nonlinearities. In the output layer, a sigmoid activation is used for binary classification, resulting in a probability score indicating the probability of a particular class. The model is able to learn hierarchical representations of input data efficiently due to its layer structure, which produces more accurate classification results. The model is compiled with the Adam optimizer, binary cross-entropy loss function, and accuracy metric for evaluation.

In the Inception-v3 algorithm, TensorFlow uses the ImageDataGenerator class to configure data generators and prepare images for training. The InceptionV3 model previously trained on the ImageNet dataset is loaded first. To adjust for binary classification problems, and remove the top classification position. Then, the model is extended with a GlobalAveragePooling2D layer to reduce spatial dimensions and extract relevant features from the input data. The fully connected Dense layers are then added to the model using the ReLU activation function. A final binary classification layer with sigmoid activation is applied to produce the desired result. All layers in this section are frozen so that they do not change during the next training phase, preserving the integrity of the pre-trained weights in the underlying InceptionV3 model. Finally, the models are compiled using ADAM optimizer, binary cross-entropy loss functions, and accuracy metrics to provide more efficient training and analysis. The results are determined by a process called fine tuning after initial training on the training dataset using a fit technique with default parameters such as a number of epochs, and batch size. This requires unfreezing some layers in the base InceptionV3 model to change their weights during subsequent training cycles. To facilitate this optimization step, the model is reassembled at a reduced number of classes by the ADAM optimizer, which allows for more precise model parameter adjustment and then further training on observing the training process and allowing its performance to change and optimize its representation in light of the uniqueness of the dataset Helps to improve.

In the SVM algorithm, preprocessed images on inception-v3 are loaded here to extract features from images. Storing image paths from the specified directory along with the accompanying directories. LabelEncoder is then used to encode these labels into numeric representations to match machine learning methods. Images are then loaded to ensure that their pixel values are the same, reduced to a fixed size of (299, 299), rotated to outline, and normalized Using a preset InceptionV3 model the trained operates on images to make predictions, which are then flattened and stored as attributes. The dataset is then divided into training and test sets, each containing different characters and features. To simplify the classification effort, an SVM classifier with linear ears is then trained on the training data to identify the underlying patterns and relationships between the retrieved and associated features.

b. Testing Module

The unlabeled image data is transferred to the test module. These models use a Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Inception-V3-based algorithm for cataract detection. These models are capable of learning features related to cataract detection as their trainable parameters start to depend on the utility of cataract detection. In order to extract features from the known shapes more efficiently, the shapes of the convolutional and fully connected layers are modified. The predicted value is then determined using the Softmax layer, also known as the output layer of the model, which determines whether the input images are classified as cataracts or not.

c. Datasets

For this paper, our team has collected data from several hospitals in Banglore and also from the internet. The below table gives the detailed data of dataset used:

	Training		Testing	
	Cataract	Non-Cataract	Cataract	Non-Cataract
Normal eye images	975	761	110	180

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Fundus images	3600	5390	400	600
Slit-Lamp images	465	487	68	49

Table 4.1: Training and Testing datasets

d. Evaluation Metrics

Evaluations in this paper are done separately for each image type for three models. This evaluation is done based on test labels which, we separated before used in testing, and on predictions obtained from the models. The accuracy Calculates the percentage of prediction accuracy among all the predictions of the model. It is determined by dividing the total number of predictions by the number of correct predictions. The Recall measures the accuracy of the model in detecting positive cases (such as spotting cataracts) from all truly positive cases. To calculate it, the ratio of true positive to false negative and true positive to both is used. The precision It measures the proportion of positive predictions that are true out of all positive predictions made by the model. True positives are calculated as the ratio of the sum of true positives and false positives. Formulas for calculating are given below.

A 2 × 2 statistic is used to represent the confusion matrix, where the diagonal cells represent actual values predicted by the system, and the other cells represent incorrect values.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

V. RESULTS

The results discussion section provides an interpretation and analysis of the main findings. and highlights the significance of the findings for cataract eye detection and the corpus of existing knowledge on the condition. The results section aims to provide an unbiased summary of the main findings, whereas the discussion section attempts to interpret and characterize the implications of these findings in light of the topic under inquiry.

Based on a number of variables, performance analysis plays a crucial role in assessing the success or failure of a cataract detection system. For the users, this implies assessing the model's accuracy and efficiency in detecting cataracts in the eye. It comprises assessing and contrasting the model's performance to the desired goals.

The system provides a straightforward workflow for cataract diagnosis through a user-friendly interface. Initially, users select the option to inspect an eye image and are prompted to upload a picture file from their storage. Once submitted, the uploaded image undergoes analysis by three distinct models: InceptionV3, Support Vector Machine (SVM), and Convolutional Neural Network (CNN). Each model independently predicts whether a cataract is present in the image. Subsequently, a majority voting mechanism determines the final prediction. If two out of the three models forecast the presence of cataracts, the image is classified as indicative of cataracts; otherwise, it is deemed free of the condition. This approach ensures a reliable and accurate diagnosis, leveraging the strengths of multiple models to enhance predictive accuracy.

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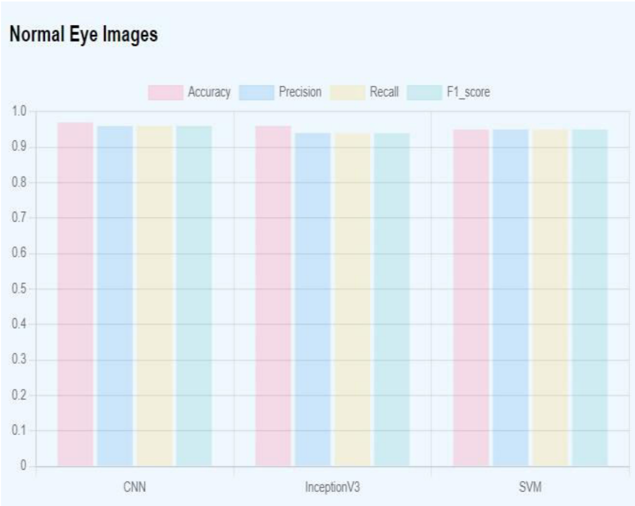

FIG. 1. COMPARISON FOR VW EYE IMAGES

FIG 2. COMPARISON FOR FUNDUS EYE IMAGES

FIG. 3.. COMPARISON FOR SLITLAMP EYE IMAGES

```
Accuracy: 0.95
Confusion Matrix:
[[ 13  29]
 [  3 597]]
Classification Report:
              precision    recall  f1-score   support

      Normal       0.81      0.31      0.45        42
    Cataract       0.95      0.99      0.97       600

    accuracy                           0.95       642
   macro avg       0.88      0.65      0.71       642
weighted avg       0.94      0.95      0.94       642
```

Fig. 4. Classification Report for Fundus eye image using cnn

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 3s 258ms/step
Accuracy: 0.97
Confusion Matrix:
[[ 68   3]
 [  3 107]]
Classification Report:
              precision    recall  f1-score   support

      Normal       0.96      0.96      0.96        71
    Cataract       0.97      0.97      0.97       110

    accuracy                           0.97       181
   macro avg       0.97      0.97      0.97       181
weighted avg       0.97      0.97      0.97       181
```

Fig. 5. Classification Report for VW eye image using cnn

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```
Accuracy: 0.96
Confusion Matrix:
[[ 28  14]
 [ 12 588]]
Classification Report:
              precision    recall  f1-score   support

      Normal       0.70      0.67      0.68        42
    Cataract       0.98      0.98      0.98       600

    accuracy                           0.96       642
   macro avg       0.84      0.82      0.83       642
weighted avg       0.96      0.96      0.96       642
```

Fig. 6. Classification Report for Fundus eye image using inception v3

```
Accuracy: 0.96
Confusion Matrix:
[[ 67   4]
 [  4 106]]
Classification Report:
              precision    recall  f1-score   support

      Normal       0.94      0.94      0.94        71
    Cataract       0.96      0.96      0.96       110

    accuracy                           0.96       181
   macro avg       0.95      0.95      0.95       181
weighted avg       0.96      0.96      0.96       181
```

Fig. 7. Classification Report for VW eye image using InceptionV3

```
Accuracy: 0.89
Confusion Matrix:
[[ 57  14]
 [  7 118]]
Classification Report:
              precision    recall  f1-score   support

    cataract       0.89      0.80      0.84        71
 noncataract       0.89      0.94      0.92       125

    accuracy                           0.89       196
   macro avg       0.89      0.87      0.88       196
weighted avg       0.89      0.89      0.89       196
```

Fig. 8. Classification Report for Fundus eye image using SVM

```
Accuracy: 0.95
Confusion Matrix:
[[190   8]
 [  8 142]]
Classification Report:
              precision    recall  f1-score   support

    cataract       0.96      0.96      0.96       198
      normal       0.95      0.95      0.95       150

    accuracy                           0.95       348
   macro avg       0.95      0.95      0.95       348
weighted avg       0.95      0.95      0.95       348
```

Fig. 9. Classification Report for VW eye image using SVM

VI. CONCLUSION AND FUTURE WORK

Utilizing three distinct types of eye images, we devised a hybrid model amalgamating CNN, InceptionV3, and SVM for cataract detection. Through rigorous training and feature extraction, our model acquired the discriminative capacity to distinguish between eyes afflicted with cataracts and those without. Compared to individual models, our method demonstrated heightened accuracy and robustness by harnessing the strengths of each component. By integrating classifications from CNN, InceptionV3, and SVM via a majority voting approach, our model ensured dependable final predictions. Evaluation metrics underscored its efficacy in accurately identifying cataracts, affirming its clinical viability. This hybrid model represents a promising advancement in automated cataract diagnosis, facilitating early identification and intervention. Future research avenues may explore optimization strategies and the integration of diverse image processing techniques to further enhance model performance. Moreover, the development of AI-powered mobile applications for remote cataract screening could extend early detection capabilities to regions with limited healthcare access. Additionally, the integration of real-time monitoring and predictive analytics into the model enables proactive cataract intervention and personalized patient care, underscoring its potential for transformative impact in ophthalmic healthcare.

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