Empirical Study on Myopia Identification Using CNN Hereditary Model for Resource Constrained Ophthalmology

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Abstract: *Refractive errors, which include myopia, hyperopia, presbyopia, and astigmatism, are common vision problems that result in blurred vision when light rays are not focused correctly on the retinal plane. Diagnosis and classification of refractive errors are essential for providing appropriate corrective measures such as glasses or contact lenses. The key objective of this research is to establish an efficient and fast approach to identifying a refractive defect and categorizing them. Leveraging the capabilities of modern technology, we utilize a smartphone's camera to capture pictures of the red reflex in the eye. During capturing, the photos are processed using recent image processing techniques to identify any irregularities or asymmetries that may indicate refractive errors. By comparing our method to other current models, we hope to illustrate the advantage of our Hereditary model, which combines a random forest and a convolutional neural network, in accurately diagnosing and classifying refractive errors. Additionally, the proposed approach can serve as a foundation in order to do additional research and development in machine learning and image processing methods improvements for the classification of ocular disorders.*

Keywords: *Refractive error, Myopia, Red reflex, Image processing, Machine learning, Hereditary model.*

Introduction

Refractive error is a common eye problem that alters how light enters one's eye and causes blurry vision in order for the eye to concentrate and focus on things at different distances, the cornea and lens must work together to bend (refract) light rays onto the retina. However, this process is hampered in those with refractive errors, leading to vision impairment [16].

World Health Organization (WHO) estimates that 153 million people worldwide have untreated refractive defects. Even though uncorrected presbyopia presumably makes up a sizable fraction of the population, it is essential to highlight that they are not included in this number. Refractive errors are estimated to account for a total of 29.6% of total visual impairment in individuals aged 0-49 and 13.4% in those 50 and older, respectively, according to the National Blindness and Visual Impairment Survey of India 2015-2019 conducted by the Ministry of Health and Family Welfare, Government of India.

Blurred vision or failure of the eye to focus clearly on an object are two of its major symptoms. The two categories of refractive error detection are autorefraction and eccentric photo refraction [19]. Autorefraction is a modern, non-invasive method for calculating refractive errors in the eyes whereas the eccentric method involves shining a light source at an eccentric angle into the patient's eye, and then using a camera to record the pattern of light reflected off the retina. Subjective, objective, and hybrid techniques can be used to measure and analyze refractive errors in the eyes [6].

Refractive errors are a severe worldwide health issue that has a huge impact on people all over the world. WHO estimates that there are 2.2 billion people in the world who suffer from a near- or far-vision impairment, highlighting the severity of the issue. Furthermore, 153 million of them suffer from refractive defects, which hinder their eyesight and everyday tasks. Both environmental and genetic factors play a role in the development of refractive errors. Regional variations exist in the prevalence of different refractive errors. Myopia and astigmatism are the most common among adults in South-East Asia, whereas hyperopia is more prevalent among both children and adults in the Americas. Failure to address these refractive errors can result in various adverse consequences [6]. Furthermore, untreated refractive errors can potentially result in more serious issues such as amblyopia (lazy eye) or even blindness, underscoring the importance of early detection and intervention [5].

The purpose of this research is to build a novel and accessible method for the detection of refractive errors in individuals using a smartphone's camera and advanced technology. The study aims to utilize the smartphone's camera flash to capture red reflex images in a dark environment. These acquired images will go through image processing techniques to enhance their features, enabling better visualization and analysis. Moreover, the study seeks to employ Machine learning (ML) methods to automatically select significant attributes from processed red reflex images. By using a classifier model, the ML algorithm will determine whether an individual has a refractive defect or a normal eye based on the extracted features.

Review of the literature

The usage of smartphones and advanced techniques in determining ocular disorders is demonstrated through a proof-of-concept smartphone application for cataract screening [2, 11]. By utilizing a smartphone with a camera and flash, it enables the general population to do early detection. As a result, practically anyone may perform self-screening, and it can also be utilized as a portable screening option in areas with few medical facilities or professionals.

A systematic review of existing approaches demonstrates [14, 17], that a number of gadgets and mobile phone applications based on changed red reflexes are being used for community screening. This data was collected from Medline database devices described in the literature including ArcLight, Portable Eye Examination Kit (PEEK), iCam (Optovue), and RetinaScope. Smartphone-based applications include CRADLE (ComputeR Assisted Detector LEukocoria), MDEyeDetector, and soft fusion classifier leukocoria detector. EyeScreen has the potential to be a useful screening tool in the regions of the world where delayed retinoblastoma diagnosis is most prevalent. A proof of concept for future uses of machine learning as well as artificial intelligence in ophthalmic applications can be offered by the reasonably strong starting performance model for machine learning with restricted training datasets in this early-stage work [2].

When capturing images for diagnostic purposes, factors such as the angle of capture, distance, and illumination must be precisely controlled to ensure accurate and reliable results. A device with adjacent viewing and illumination systems that are close enough to one another to allow reflex formation while staying far enough away to allow crescents can detect refractive errors just as well as a direct ophthalmoscope [3]. Pamplona et al. [13] demonstrated an interactive technique based on a brand-new near-eye optical probe and high-resolution display asserting that this is the sole technique for estimating wave front aberrations devoid of retinal illumination or moving elements. Astigmatism and high hyperopia can be detected more accurately with near visual acuity (NVA) than with distance visual acuity (DVA), but high myopia can be detected more accurately with DVA than NVA. In conclusion, the series of DVA and NVA tests performed better at the detection of serial refractive errors than one or both of the tests run separately [10].

Refractive defects, such as hyperopia, myopia, and astigmatism, can change the red reflex, resulting in an abnormally asymmetric and nonhomogeneous red reflex, as demonstrated by Jin et al. [10]. The colour of the reflected asymmetry that is discernible through the ophthalmoscope's aperture can aid in locating the issue. Fageeri et al. [7] determined that identifying eye disorders is now an important concern of real-world medical issue. Early detection of eye conditions can stop complications and blindness [19] demonstrated the effectiveness of the residual network (REDNet), a neural network for detecting refractive errors that not only extracts the attributes of each image but also completely exploits the contextual relationship across images. In comparison to existing deep learning-based systems, the refractive error prediction method suggested in this study displayed great accuracy and the capacity to forecast spherical power, cylindrical power, and spherical equivalent. Fu et al. [9] demonstrated how trained gaze estimation model characteristics from convolutional neural network (CNN) provide information about human eyes. The Refractive Error Detection Network is built by combining CNN and recurrent neural network (RNN) for REDNet model, as demonstrated from multiple photorefraction images. To extract contextual links between feature sequences, estimate the spherical power, cylindrical power, and spherical equivalent, and effectively employ features that incorporated six-direction diopter information, long short-term memory (LSTM) was required.

Materials and methods

In this study, a comprehensive approach was adopted to develop an accurate refractive error detection model. The dataset was meticulously preprocessed and augmented to ensure optimal performance during training. To enhance the image's features, the eye region with red-colored pupils was cropped, and a series of preprocessing steps were applied. Augmentation techniques were then used to normalize the dataset, enhancing its robustness.

The core of the proposed methodology lies in the Hereditary model, a combination of two distinct models, which was applied to train the dataset. The Hereditary model effectively identified and classified images into two categories: normal eye and myopia-conditioned eye. This classification process was achieved through systematic workflow, as illustrated in Fig. 1.

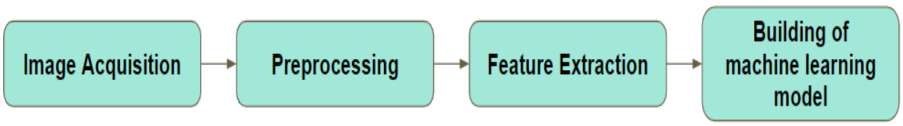


Fig. 1 Proposed methodology

Each model in the Hereditary was trained individually, and their collective accuracy was evaluated once the models were applied to the dataset. The results showcased the model's successful performance in accurately classifying refractive eye conditions. Metrics such as accuracy, precision, recall, sensitivity, and specificity were used to gauge model effectiveness. Furthermore, the different models employed in the study were compared based on their testing accuracy. Through rigorous evaluation, the best-performing model was selected for the final classification process.

Dataset

A carefully selected dataset of 110 eye pictures was used to train in the current research and evaluate the model performance. The dataset comprised 65 images of normal eyes and 45 images of eyes with myopia. To ensure diverse representation, the pictures were taken in various locations. Reflecting different subject refractive error conditions.

The images were captured using a "Samsung Galaxy A22" smartphone with a 12 megapixels camera and an image resolution 3000×4000 pixels. The smartphone's flash was enabled during the image capture process to illuminate the subject eye. The camera distance was standardized at 1.5 meters as shown in Fig. 2, and the angle was adjusted between 10 to 20 degrees, depending on the subject height.

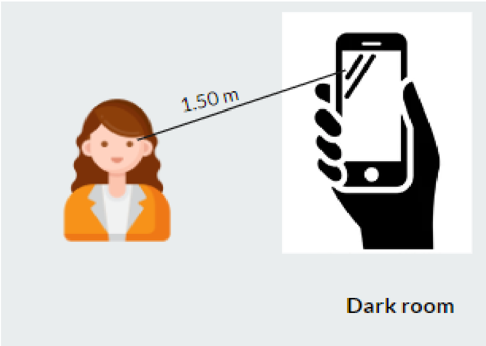


Fig. 2 Image captured at 1.5 m distance

The dataset consisted of images collected from children attending Bharatiya Grameen Mahila Sangh (BGMS) Shishukunj Vidyalaya School and adults from various locations, including BMS College of Engineering, Ramaiah Hospital, friends, and family. Among these, 68 photos were taken of children aged 7 to 15, and 42 images were taken of individuals older than 18.

During the training of the dataset, certain images were excluded for the following reasons:

- Individuals who didn't pass an eye test were eliminated to ensure accuracy and reliability.
- Images of individuals with other eye disorders, such as cataract or hyperopia were also excluded to focus solely on refractive error detection.
- Images with blurred or obscured red eyes were not considered to maintain data quality and consistency.

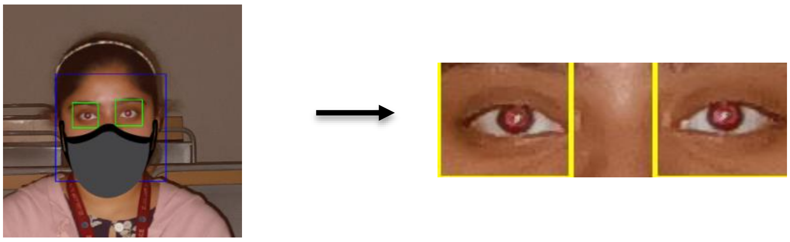
By meticulously curating the dataset and including a diverse range of eye images, this study ensures a robust and reliable training process for the model, promising accurate refractive error detection and assessment.

Image preprocessing

The preprocessing step plays a crucial role in refining the image data for accurate analysis and model training. It aims to eliminate noise and variations while improving the overall image quality. To achieve this, several essential processes were employed.

Initially, for image clarity, improvement was performed with image enhancement procedures. Additionally, image normalization and non-uniform intensity correction were implemented to eliminate artefacts and ensure more precise processing steps.

To focus specifically on the eye region, the images were cropped and resized to a standardized dimension of 224×224 pixels, so only the eyes are visible (see Fig 3). Techniques for data augmentation were employed to reduce potential overfitting concerns, enhancing the model's ability to generalize to unseen data. Image enhancement procedures, including adjustments to brightness, contrast, and sharpness, were utilized to further improve the visual quality of the images.



A) B)

Fig. 3 A) Haar cascade classifier detecting face and eyes;
B) eyes image, cropped and resized to 224×224 pixels.

The distribution of the data was made consistent by normalizing the images, which also made it possible for the training phase convergence to occur more quickly.

To build robust training models capable of handling diverse real-world scenarios, the dataset underwent normalization process that followed normal (statistical) distribution. This approach aimed to take into account differences brought on by difficult lighting situations and to take photographs that may not have been properly taken in such situations.

The preprocessing steps undertaken in this study collectively contribute to enhancing the accuracy and resilience of the model, enabling effective refractive error detection even in instances of noise and challenging environmental conditions.

Feature extractor and classifier

The Hereditary model used in this study is an effective combination of CNN and RF. CNN is a commonly used approach for picture classification and identification applications, providing effective feature representation in the field of analysis of images. However, CNN can be computationally intensive during training, resulting in longer training times [20]. The CNN architecture utilized in this model consists of multiple layers designed for feature extraction and classification tasks. The input layer expects images with a specific height, width, and three color channels corresponding to the RGB system. This is followed by three sets of convolutional layers, each set comprising a convolutional layer with ReLU activation function and subsequent max pooling layer to down sample the feature maps. The first convolutional layer applies 32 filters, the second applies 64 filters, and the third applies 128 filters.

After the convolutional layers, the feature maps are flattened into 1D vector using a flattened layer, followed by a fully connected layer with 128 neurons and a ReLU activation function. Finally, the output layer consists of a single neuron with a sigmoid activation function, suitable for binary classification tasks, producing the probability of the input image belonging to the positive class.

In contrast, RF is renowned for its quick training speed and good classification accuracy, making it a desirable option. RF addresses the issue of excessive fitting that may arise with individual decision trees and exhibits robustness to noise and anomalies. It efficiently handles large datasets and performs effectively [4, 5, 18]. RF classifier is instantiated with 100 decision trees using the RF classifier class from the scikit-learn library. This classifier is trained on features extracted from the CNN model.

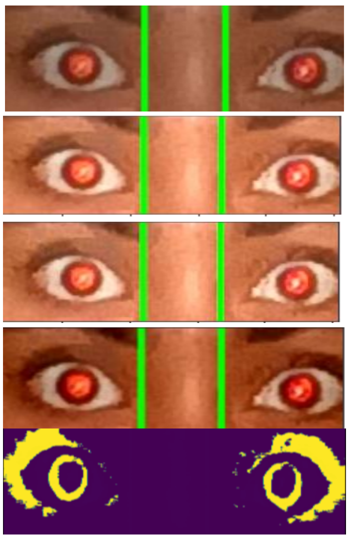
In the hybrid model, the output layer of CNN, which comprises extracted features, is passed on to the RF classifier for final classification. CNN operates by employing multiple filters on specific regions of the image, detecting fundamental features such as edges and corners. Secondary pooling layers further extract essential features after each convolutional layer, enhancing the representation. RF acts as a complementary classifier, combining the strengths of CNN's feature extraction with its own speedy and accurate classification capabilities. This fusion of CNN and RF exploits the advantages of both models, leading to improved performance speed and reduced risk of overfitting.

The hybrid model effectively leverages CNN's ability to automatically extract relevant features and utilizes RF's efficiency in classification. By doing so, it mitigates the prolonged training time typically associated with CNN, while achieving enhanced classification accuracy. This approach proves highly valuable tasks in image analysis, allowing faster and more accurate predictions without compromising the quality of results.

Results and discussion

Image preprocessing

An effective method for locating particular objects or features in photos is the Haar cascade classifier [12]. It works very well at identifying faces and eyes in photos. In preprocessing stage, cropped photos underwent crucial transformations (Fig. 4).



A) resizing into 255×255 pixels

B) data augmentation: brightness

C) data augmentation: sharpness

D) data augmentation: contrast

E) normalized image

Fig. 4 Preprocessing procedures performed on the images

Photos were scaled to a normalized range of 0 to 1 and resized to 255×255 pixels, ensuring consistency in the input data. In image enhancement and manipulation, brightness, contrast, and saturation are crucial factors. It was advantageous to increase brightness for pictures that were either poorly contrasted or taken in low light. To highlight details and boost visual quality overall, sharpness augmentation was effective with fuzzy photos. It was helpful to utilize contrast enhancement to enhance an image's texture and features as well as the visual separation of items [13].

Finally, the standardization procedure, which involves taking the mean and dividing it by the standard deviation, was used to conduct normalization. By ensuring that the input data has consistent scales, normalizing images may speed convergence during training and increase generalization.

Performance evaluation

In the performance evaluation phase, a Hereditary model comprising the CNN-based RF model was employed to assess its effectiveness compared to individual models [18]. The scikit-learn library's training-test split method was utilized, dividing the data into an 80:20 ratio, with 80% allotted for training and 20% for testing.

The Hereditary model, a combination of the CNN and RF models, exhibited remarkable optimization compared to running the models separately. The dataset of 110 images was preprocessed and normalized, ensuring consistency in the pixel values between 0 and 1.

The CNN model evaluation dataset was divided into training, validation, and testing sets with a ratio of 6:2:2 using an equal number of normal and myopic eye photos (a total of 110 images). The data was divided with the help of the scikit-learn selection model. Data was input into the CNN model once the dataset was sampled, and the training accuracy and loss were then determined. For binary classification in the CNN model, sigmoid activation was used, which employs an Adams optimizer with a learning rate of 0.001 was used. The binary cross-entropy loss function was chosen to predict losses.

During the initial training phase, the Hereditary model achieved a training accuracy of 0.45 with a loss of 1.934 and a validation accuracy of 0.50 with a loss of 0.95. As the training progressed with increasing epochs, both accuracy and loss experienced significant improvements. Ultimately, the Hereditary model attained an impressive training accuracy of 1.0 with a minimal loss of 0.019.

For the testing phase, the Hereditary model, incorporating both the CNN and RF components, demonstrated outstanding performance, achieving a testing accuracy of 0.9545. These results highlight the effectiveness of combining the strengths of CNN and RF to enhance predictive capabilities and ultimately yield a highly accurate and reliable Hereditary model for the image classification task.

In the individual models, the CNN achieved a training accuracy of 0.80, while the RF achieved a testing accuracy of 45.45%. However, the real power of the Hereditary model, which combined both CNN and RF, was demonstrated by its remarkable training accuracy of 1.0 and an impressive testing accuracy of 95.45%. This significant improvement in accuracy highlights the effectiveness of the Hereditary approach, leveraging the strengths of both models to achieve superior results in image classification. The accuracy of different models is given in Table 1.

Table 1. Accuracy of different models

	Training accuracy	Testing accuracy
CNN Model	84.73%	54.00%
RF	n.a.	45.00%
CNN + RF	100%	95.45%

The training loss graph with accuracy and validation loss is shown in Fig. 5 and Fig. 6. This model showed much improvement in the accuracy with CNN and trained faster using the RF classifier.

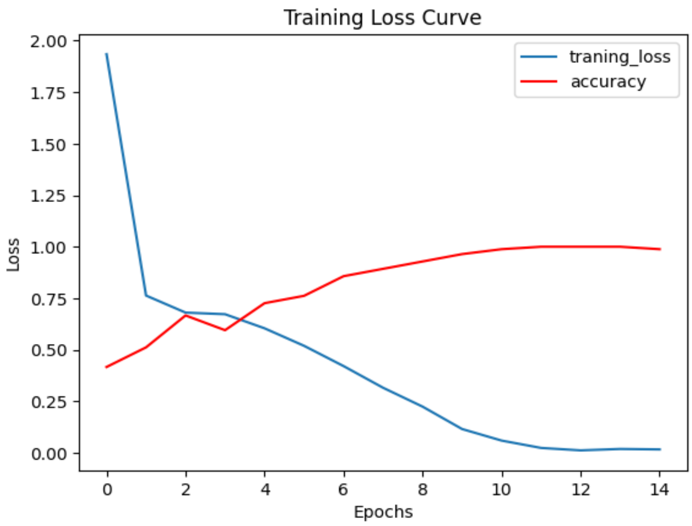


Fig. 5 Training loss graph with accuracy

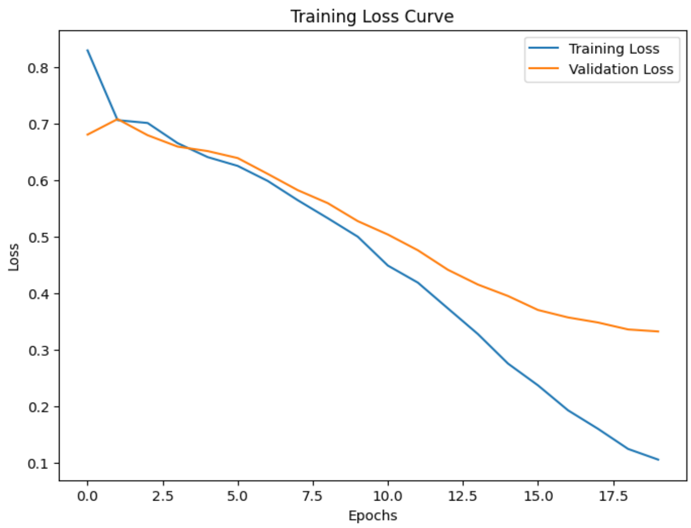


Fig. 6 Validation loss graph

The calculations for accuracy, precision, recall, F1 score, sensitivity, specificity, and receiver operating characteristic (ROC) curve were performed following standard methodologies as described in the literature [1, 8, 15]. Accuracy was calculated as the ratio of correctly predicted instances to the total number of instances. Precision, recall, and F1 scores were computed based on the confusion matrix, which summarizes the counts of true positive, true negative, false positive, and false negative predictions. Sensitivity (true positive rate) and specificity (true negative rate) were calculated from the confusion matrix. A confusion matrix for the

Hereditary model is shown in Fig. 7. The following formulae in Eq. (1) to Eq. (6), represent the performance measures. In all equations *TP* is true positive, *FN* – false negative, *TN* – true negative and *FP* – false positive.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1 score} = \frac{2\times(\text{Precision}\times\text{Recall})}{(\text{Precision}+\text{Recall})} \tag{4}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{5}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{6}$$

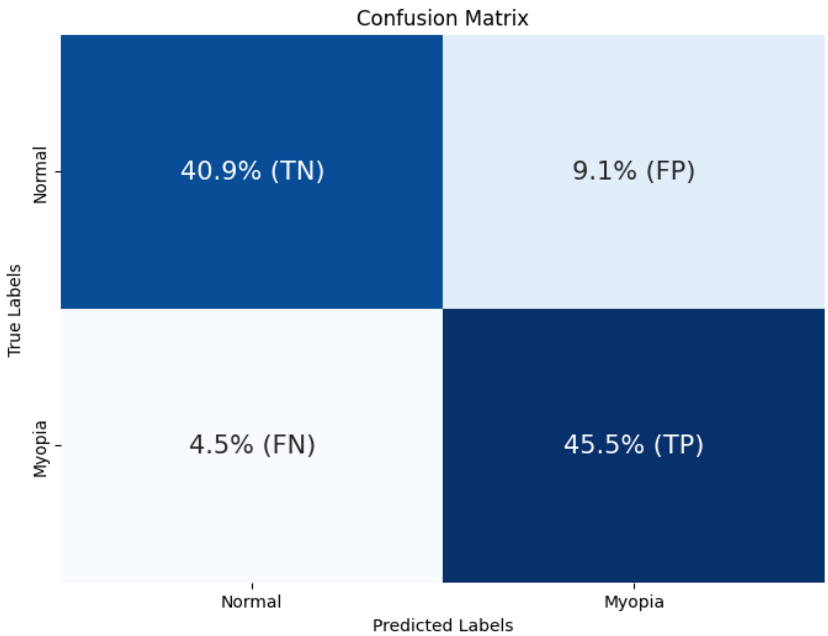


Fig. 7 Confusion matrix for Hereditary model

The overall performance matrix for the model is shown in Table 2. The Hereditary model exhibited outstanding accuracy, achieving a remarkable accuracy rate of 95.45%. This emphasizes its capability to make accurate predictions across both classes and highlights its suitability for tasks that demand high precision in decision-making. Furthermore, the Hereditary model excelled in precision, attaining a perfect precision score of 100%, indicating its minimal tendency for false positive predictions. The high recall of 90.90% showcases the model's ability to effectively capture true positive instances, enhancing its reliability in correctly identifying positive cases. The F1 score, harmonizing precision and recall, reinforces the Hereditary model's robust performance, registering an impressive value of 95.23%. The acquired sensitivity and specificity are, respectively, 90.90% and 72.72%.

Table 2. Performance metrics of the Hereditary model

Model	Hereditary model
Accuracy (%)	95.45
Precision (%)	100
Recall (%)	90.90
F1 score (%)	95.23
Sensitivity (%)	90.90
Specificity (%)	72.72

The receiver operating characteristic (ROC) curve takes both true outcomes from the test set and predicted possibilities from the trained model for positive class. The area under curve (AUC) taken for a random classifier is 0.5 and the value racing 1 indicates a perfect classifier. In this Hereditary model, the ROC-AUC obtained for the given dataset is about 0.94. Fig. 8 indicates the classifier's ability to discriminate between positive and negative instances.

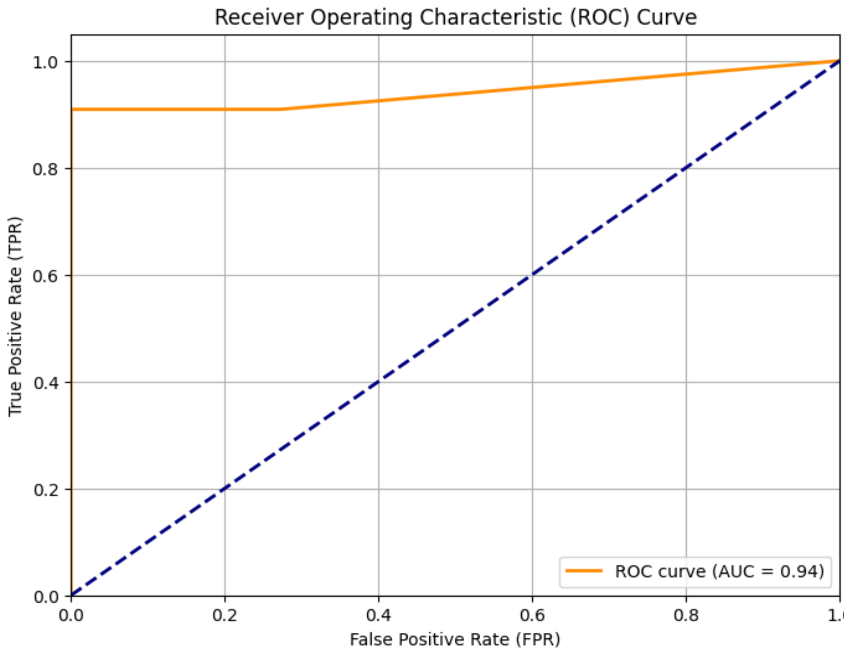


Fig. 8 Receiver operating curve for the model

Comparison with other models

In this work, the pre-trained models were systematically compared to several other models that complied with reference publications. The evaluation involved analyzing different models and their respective performance metrics. All the models were trained using a similar preprocessed dataset to ensure a fair comparison. This standardized preprocessing aimed to minimize bias and enable a direct comparison of model performance. By employing consistent preprocessing, the model's strengths and weaknesses were assessed accurately. Ultimately, this approach facilitated informed decisions regarding model selection and Hereditary construction, leading to meaningful conclusions about overall system performance. For instance, Resnet was trained with 48 epochs, whereas visual geometry group (VCG) was trained with 10 epochs. The outcomes of this model comparison, as well as their performance metrics, are presented in Table 3, shedding light on the strengths and weaknesses of each model based on their respective performance metrics.

Table 3. Performance metrics of the Hereditary model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Hereditary model	95.45	100	90.90	95.23
Resnet	41.30	14.06	37.50	20.45
Densenet	63.64	71.00	29.00	41.00
Mobilenet	45.45	25.00	20.00	22.00
VGG	62.50	38.54	45.83	38.94

From Table 3, it is evident that CNN architecture is commonly employed in eye disease recognition tasks, but the accuracy achieved was generally below 90%. However, the usage of the Hereditary model in the current work distinguishes it, which yielded a significantly higher accuracy of 95.45%.

In contrast, the Resnet architecture exhibited comparatively lower performance metrics. While its accuracy stood at 41.30%, its precision, recall, and F1 score were markedly lower, at 14.06%, 37.50%, and 20.45%, respectively. This indicates a challenge in capturing true positive instances and maintaining precision, which could be attributed to issues related to feature extraction or model complexity.

Densenet showed an accuracy of 63.64%, a precision of 71.00%, a recall of 29.00%, and an F1 score of 41.00%. The better precision demonstrates its capacity to categorize positive instances accurately, but the relatively lower recall implies there is still potential for development in terms of precisely capturing all actual positive instances.

There were differences in performance between the Mobilenet and VGG architectures. Both models showed lower precision, recall, and F1 scores, with Mobilenet achieving an accuracy of 45.45% and VGG reaching 62.50%. Complex feature handling difficulties or class imbalances may be the reason for these outcomes.

Among all the studies mentioned in the table, our results demonstrate a more accurate and precise classification of myopia and normal eye conditions. The Hereditary model's exceptional performance showcases its potential for improving eye disease recognition and further emphasizes the importance of combining CNN and RF models to enhance classification accuracy in this domain.

Conclusion

Capturing images through smartphones is a non-invasive, time-efficient process that easily integrates into an individual's daily life. This unique blend of accessibility, accuracy, and user-friendliness underscores the disruptive potential of this approach. This method takes smartphones' widespread use to undertake precise refractive error evaluations conveniently and cost-effectively. It is not only a technical advancement but a societal one, promising to redefine how we approach vision diagnostics and opening new horizons for improved eye care accessibility worldwide. The proposed Hereditary model, leveraging a combination of CNN and RF designs, exhibits remarkable performance in detecting refractive errors, specifically myopia, from red reflex eye images. Before feeding the images into the CNN for feature extraction, various preprocessing techniques were applied to enhance the input data quality. This preprocessing step significantly contributed to the model's accuracy and robustness.

Through the implementation of the Hereditary model, the study successfully classified different types of refractive errors and precisely predicted whether an eye has myopia or is considered as normal. In comparison to other models utilized in this research, the Hereditary model outperformed them, achieving the highest accuracy of 95.45% for distinguishing between normal and myopic conditions. The model's overall performance metrics, including precision, recall, and F1 score, also demonstrated superior efficiency and effectiveness.

One of the most appealing aspects of this method is its versatility. It not only surpasses existing CNN-based ocular disease classification models but also demands less processing time, making it more efficient and suitable for real-time applications. Furthermore, the model can be easily extended to tackle other types of medical image-based disease classification tasks, showcasing its potential for broader medical applications. Moreover, the study explores the possibility of applying ocular image segmentation to further improve the model's accuracy and specificity. With a diverse set of images, the model could be extended to classify other refractive errors with comparable success.

Overall, this proposed Hereditary model presents a significant advancement in the field of eye disease recognition. Its implementation promises to be immensely beneficial for medical experts, revolutionizing eye illness diagnostics. While the model has already demonstrated impressive performance, continuous research and exploration hold the potential for further advancements and the expansion of its application in the future.

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