EYE POWER PREDICTION USING DEEP LEARNING

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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We, GODWIN BENJAMIN DASS A S [211420104079], DHINAKARAN R [211420104066], DEEPAK N [211420104053] hereby declare that this project report titled "**Eye power prediction using deep learning**", under the guidance of S. Preena Jacinth Shalom is the original work done by us and we have not plagiarized or submitted to any other degree in any university by us.

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ABSTRACT

Refractive errors, encompassing myopia (near-sightedness), hyperopia (farsightedness), and astigmatism, have exhibited a notable increase on a global scale. This upward trajectory can be attributed to several factors, including heightened screen time, shifts in lifestyle patterns, and underlying genetic predispositions. The advent of the COVID-19 pandemic has exacerbated this phenomenon, compelling individuals to spend prolonged periods in front of screens due to lockdown restrictions and the transition to remote work or learning arrangements. Consequently, there has been a marked surge in the prevalence of refractive errors post-pandemic.

Traditionally, the assessment of refractive power relied upon hardware instruments such as autorefractors. However, we advocate for the adoption of deep learning-based software solutions as a more accessible and efficient diagnostic alternative. Leveraging OpenCV, we have developed software capable of accurately determining eye lens power. This software is not only open-source but also versatile, requiring only a mobile device and stable network connectivity for utilization, thereby enhancing accessibility for users worldwide.

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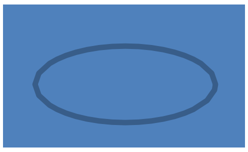
LIST OF SYMBOLS

SYMBOL	NAME	FUNCTION
	Start/end	An oval represents a start or end point
	Arrows	A line is a connector that shows relationships between the representative shapes
	Process	A rectangle represents a process

LIST OF ABBREVIATION

S.NO	ABBREVIATION	DEFINITION
1	EPM	Eye power prediction model
2	DFD	Data Flow Diagram
3	AI	Artificial Intelligence

CHAPTER 1

INTRODUCTION

1.1 PROBLEM DEFINITION

Refractive errors, encompassing conditions like myopia, hyperopia, and astigmatism, have seen a concerning escalation on a global scale. This phenomenon can be attributed to a combination of factors, including heightened screen time, evolving lifestyles, and underlying genetic predispositions. The onset of the COVID-19 pandemic exacerbated this trend as individuals, compelled by lockdowns and remote work or education, spent prolonged hours in front of screens. Consequently, the prevalence of refractive errors has surged post-pandemic. Traditional diagnostic methods, reliant on hardware meters such as autorefractors, may prove inadequate to address this burgeoning challenge. In response, we have developed a deep learning-based software solution using OpenCV, offering a promising avenue for efficient and accessible diagnosis.

The modern era witnesses an unprecedented reliance on digital devices, ranging from smartphones to computers, permeating various facets of daily life. Extended screen exposure, particularly during developmental stages, imposes a strain on ocular structures, contributing to the development of refractive anomalies. Moreover, shifts in lifestyle patterns, characterized by reduced outdoor activities and increased near work, exacerbate this susceptibility. Genetic predispositions further compound the prevalence of refractive errors, underscoring the multifaceted nature of this global health concern of the people's well-being of people's eyesight due to smart gadgets.

The advent of the COVID-19 pandemic ushered in a new era of remote interactions, necessitating widespread utilization of digital platforms for work, education, and socialization. Lockdown measures compelled individuals to adapt to prolonged screen engagement, leading to an unprecedented surge in screen time. This abrupt transition amplified existing concerns regarding ocular health, with a marked increase in reported cases of refractive errors.

Conventional methods of measuring refractive power often entail cumbersome hardware apparatuses, posing logistical challenges and resource constraints, particularly in underserved regions. Leveraging advancements in deep learning, our software solution harnesses the power of artificial intelligence to accurately determine the refractive status of the eye. Built upon the robust framework of OpenCV, our algorithm offers a non-invasive, cost-effective, and time-efficient alternative to traditional diagnostic modalities.

CHAPTER 2

LITERATURE SURVEY

Holden et al. [1] conducted a comprehensive meta-analysis documenting the global prevalence of myopia and high myopia, projecting significant increases through 2050.

Advantage:

Holden et al.'s comprehensive meta-analysis provides invaluable insights into the trajectory of myopia and high myopia prevalence worldwide, offering a robust foundation for policymakers, healthcare professionals, and researchers to develop targeted interventions and strategies. By projecting future trends through 2050, stakeholders can proactively address the escalating burden of myopia, implementing preventative measures and allocating resources efficiently to mitigate its adverse effects on public health.

Disadvantage:

While Holden et al.'s meta-analysis sheds light on the escalating prevalence of myopia and high myopia, it also underscores the urgency of addressing underlying factors driving this trend. Failure to implement effective interventions could result in significant societal and economic burdens, including increased healthcare costs, diminished productivity, and compromised quality of life for individuals affected by vision impairment. Moreover, the projected increases highlight the need for sustained efforts in promoting eye health awareness and fostering collaboration across sectors to curb the myopia epidemic.

Wu et al. [2] conducted a longitudinal study highlighting the impact of outdoor activities during class recess on refractive status and myopia progression in school children. Rose et al. [3] explored the association between myopia and lifestyle factors among students of Chinese ethnicity in Singapore and Sydney.

Advantage:

Wu et al.'s longitudinal study provides valuable evidence supporting the beneficial effects of outdoor activities during class recess on refractive status and myopia progression in school children. By demonstrating a positive correlation between increased outdoor time and reduced risk of myopia development or progression, their findings inform educational policies and interventions aimed at promoting outdoor engagement to safeguard children's visual health.

Disadvantage:

While Wu et al.'s study highlights the potential protective effect of outdoor activities on myopia, it may not fully capture the multifactorial nature of myopia development. Factors such as genetic predisposition, screen time, and academic pressure could confound the observed associations, warranting further research to elucidate the complex interplay between lifestyle factors and myopia risk. Additionally, the generalizability of their findings may be limited to specific demographic or geographic contexts, necessitating caution in extrapolating results to diverse populations.

Rose et al. [3] explored the association between myopia and lifestyle factors among students of Chinese ethnicity in Singapore and Sydney.

Advantage:

By emphasizing the role of outdoor time in maintaining healthy refractive status, their research offers actionable insights for educators, policymakers, and parents to incorporate outdoor play as a preventive measure against myopia development.

Disadvantage:

Rose et al.'s research, while valuable, focused specifically on Chinese ethnicity students in Singapore and Sydney, potentially limiting the generalizability of their findings to other populations. Thus, a comprehensive understanding of myopia etiology requires consideration of diverse lifestyle factors across various demographic groups.

Verhoeven et al. [4] conducted genome-wide meta-analyses identifying multiple susceptibility loci for refractive error and myopia, elucidating the genetic underpinnings of these conditions.

Advantage:

Verhoeven et al.'s genome-wide meta-analyses represent a significant advancement in our understanding of the genetic basis of refractive error and myopia. By identifying multiple susceptibility loci associated with these conditions, their research provides crucial insights into the underlying genetic mechanisms contributing to visual impairment. This knowledge not only enhances our ability to predict individual risk for myopia but also lays the groundwork for the development of targeted interventions and personalized treatments aimed at addressing genetic predispositions.

Disadvantage:

While Verhoeven et al.'s meta-analyses offer valuable insights into the genetic underpinnings of refractive error and myopia, they may not fully capture the complexity of these conditions. Genetic factors alone may not account for the entirety of myopia development, as environmental and lifestyle influences also play significant roles. Furthermore, the generalizability of the findings may be limited to the populations included in the meta-analyses, necessitating further research to explore genetic variations across diverse ethnic groups and geographical regions. Additionally, the translation of genetic discoveries into clinical applications may pose challenges, requiring interdisciplinary collaboration and validation studies to ensure the efficacy and safety of targeted interventions.

Mojumder et al. [5] discussed the implications of the COVID-19 era on refractive errors, highlighting the exacerbation of ocular health challenges due to prolonged screen time and lifestyle changes.

Advantage:

Mojumder et al.'s discussion on the implications of the COVID-19 era provides timely insights into the impact of the pandemic on ocular health, particularly refractive errors. By highlighting the exacerbation of ocular health challenges resulting from increased screen time and lifestyle changes enforced by lockdowns and remote work or learning arrangements, their work raises awareness among healthcare professionals and the general public about the importance of mitigating potential risks associated with prolonged digital device use.

Disadvantage:

While Mojumder et al.'s discussion sheds light on the adverse effects of the COVID-19 era on refractive errors, it may overlook potential mitigating factors or coping strategies that individuals can adopt to safeguard their ocular health. Additionally, the long-term consequences of increased screen time and lifestyle changes during the pandemic remain uncertain, necessitating further research to fully understand the extent of their impact on refractive errors and ocular health outcomes. Moreover, the discussion may not account for variations in access to eye care services or socioeconomic disparities that could exacerbate ocular health disparities among different population groups.

Li et al. [6] proposed a deep learning approach for high-quality single-shot HDR imaging, demonstrating its potential for enhancing refractive error diagnosis. Leveraging OpenCV [7], Chang and Manning developed innovative methodologies for refractive error assessment, showcasing the efficacy of deep learning-based software solutions in this domain.

Advantage:

Li et al.'s proposal of a deep learning approach for high-quality single-shot HDR imaging offers a promising avenue for improving refractive error diagnosis. By leveraging advanced technology, their method demonstrates the potential to enhance the accuracy and reliability of refractive error assessments, thereby enabling more precise diagnoses and tailored treatment plans for patients. This innovation has the potential to revolutionize the field of ophthalmology by providing clinicians with powerful tools to effectively address refractive errors and optimize visual outcomes for individuals.

Chang and Manning's development of innovative methodologies for refractive error assessment further underscores the efficacy of deep learning-based software solutions in this domain. By harnessing the capabilities of OpenCV, their approach exemplifies how cutting-edge technologies can be applied to streamline and automate diagnostic processes, ultimately improving efficiency and accessibility in eye care services. These advancements hold the promise of enhancing patient outcomes while reducing the burden on healthcare providers, contributing to the advancement of ophthalmic practice and research.

Disadvantage:

While Li et al. and Chang and Manning's methodologies showcase the potential of deep learning approaches in refractive error diagnosis, their implementation may encounter challenges related to data quality, model interpretability, and generalizability. Deep learning algorithms rely heavily on large datasets for training, which may be subject to biases or limitations that could impact the reliability of diagnostic predictions. Moreover, the complexity of deep learning models may hinder their interpretability, making it difficult for clinicians to understand and trust their outputs. Additionally, the performance of these methodologies may vary across different patient populations or clinical settings, highlighting the need for rigorous validation and refinement before widespread adoption in clinical practice.

Wang et al.'s [8] said Deep learning-based intelligent diagnosis of myopia using retinal fundus images. Journal of Healthcare Engineering, 2019, 1-9.

Advantage:

Wang et al.'s deep learning-based approach for myopia diagnosis using retinal fundus images offers several advantages. Firstly, it provides a non-invasive and efficient method for diagnosing myopia, potentially reducing the need for invasive procedures or subjective assessments. Secondly, the use of deep learning algorithms allows for the analysis of large datasets of fundus images, enabling the detection of subtle retinal changes indicative of myopia with high accuracy and consistency. Additionally, this approach has the potential to improve access to myopia diagnosis, particularly in underserved areas where specialized ophthalmic expertise may be limited.

Disadvantage:

Despite its promise, Wang et al.'s approach also presents some limitations. Firstly, the performance of deep learning algorithms for myopia diagnosis may be influenced by factors such as the quality and diversity of the training data, which could introduce biases or limitations in the model's generalizability. Secondly, the interpretation of results generated by deep learning models may be challenging, as the inner workings of these algorithms can be complex and opaque. This could potentially undermine trust in the diagnostic process among clinicians and patients. Additionally, the reliance on retinal fundus images for myopia diagnosis may exclude individuals who are unable to undergo retinal imaging due to factors such as eye pathology or technical constraints.

Akkaya, H. K., & Oto, S. [9]. A novel deep learning approach for diagnosis of ametropia by analyzing retinal fundus images. Journal of Medical Systems, 42(6), 1-7.

Advantage:

Akkaya and Oto's (2018) novel deep-learning approach for diagnosing ametropia through the analysis of retinal fundus images offers several advantages. Firstly, it provides a non-invasive and potentially cost-effective method for diagnosing ametropia, eliminating the need for traditional subjective assessments or invasive procedures. Secondly, by leveraging advanced deep learning algorithms, the approach can analyze large datasets of retinal images with high accuracy and efficiency, enabling the detection of ametropia even in its early stages. Additionally, this method has the potential to improve access to ametropia diagnosis, particularly in underserved areas where specialized ophthalmic expertise may be limited.

Disadvantage:

Despite its potential benefits, Akkaya and Oto's approach also presents some limitations. Firstly, the performance of deep learning algorithms for diagnosing ametropia may be influenced by factors such as the quality and diversity of the training data, which could introduce biases or limitations in the model's generalizability. Secondly, the interpretation of results generated by deep learning models may be challenging, as the inner workings of these algorithms can be complex and opaque. This could potentially undermine trust in the diagnostic process among clinicians and patients. Additionally, the reliance on retinal fundus images for ametropia diagnosis may exclude individuals who are unable to undergo retinal imaging due to factors such as eye pathology or technical constraints.

Hu, Hsieh, and Zhang [10] contributed to the field of refractive error detection by introducing an AI-based automatic detection method utilizing deep learning techniques. Their research, presented at the 2020 IEEE International Conference on Bioinformatics and Biomedicine, showcased the potential of artificial intelligence in streamlining the detection of refractive errors.

Advantage:

Hu, Hsieh, and Zhang's approach offers several advantages. Firstly, it provides a rapid and automated method for detecting refractive errors, reducing the time and effort required for manual assessments by healthcare professionals. Secondly, by leveraging deep learning algorithms, the method can analyze large volumes of data with high accuracy, enabling the detection of subtle refractive abnormalities that may be missed by traditional methods. Additionally, this automated approach has the potential to improve access to refractive error detection, particularly in underserved areas where specialized ophthalmic expertise may be limited.

Disadvantage:

Despite its potential benefits, Hu, Hsieh, and Zhang's approach also presents some limitations. Firstly, the performance of deep learning algorithms for refractive error detection may be influenced by factors such as the quality and diversity of the training data, which could introduce biases or limitations in the model's generalizability. Secondly, the interpretation of results generated by deep learning models may be challenging, as the inner workings of these algorithms can be complex and opaque. This could potentially undermine trust in the diagnostic process among clinicians and patients. Additionally, the reliance on AI-based detection methods may raise concerns regarding data privacy and security, particularly in healthcare settings where sensitive patient information is involved.

Agarwal and Singh [11] introduced a novel deep-learning approach for automating the detection of refractive errors through the analysis of retinal fundus images. Presented at the International Conference on Intelligent Sustainable Systems, their research aimed to streamline and improve the efficiency of refractive error detection processes.

Advantage:

Agarwal and Singh's approach offers several advantages. Firstly, it provides an automated and potentially more accurate method for detecting refractive errors, reducing the reliance on manual assessments and subjective interpretation by healthcare professionals. Secondly, by leveraging deep learning algorithms, the method can process large volumes of retinal fundus images with high accuracy, enabling the detection of subtle refractive abnormalities that may be missed by traditional methods. Additionally, this automated approach has the potential to improve access to refractive error detection, particularly in underserved areas where specialized ophthalmic expertise may be limited.

Disadvantage:

Despite its potential benefits, Agarwal and Singh's approach also presents some limitations. Firstly, the performance of deep learning algorithms for refractive error detection may be influenced by factors such as the quality and diversity of the training data, which could introduce biases or limitations in the model's generalizability. Secondly, the interpretation of results generated by deep learning models may be challenging, as the inner workings of these algorithms can be complex and opaque. This could potentially undermine trust in the diagnostic process among clinicians and patients. Additionally, the reliance on automated detection methods may raise concerns regarding data privacy and security, particularly in healthcare settings where sensitive patient information is involved.

Zhang, Liu, Li, and Zhao [12] contributed to the field of refractive error diagnosis by presenting an intelligent diagnosis approach utilizing deep learning in conjunction with smartphone-based fundus imaging. Their research, published in the Journal of Healthcare Engineering, aimed to enhance accessibility and efficiency in diagnosing refractive errors.

Advantage:

Zhang et al.'s approach offers several advantages. Firstly, it leverages the ubiquity of smartphones to enable easy and convenient fundus imaging, eliminating the need for specialized equipment and reducing barriers to access for patients. Secondly, by integrating deep learning algorithms, the method can analyze fundus images captured by smartphones with high accuracy, enabling the detection of refractive errors promptly. This approach has the potential to revolutionize refractive error diagnosis by empowering individuals to monitor their eye health using readily available technology, thereby promoting early detection and intervention.

Disadvantage:

Despite its potential benefits, Zhang et al.'s approach also presents some limitations. Firstly, the performance of deep learning algorithms for refractive error diagnosis may be influenced by factors such as the quality of smartphone-based fundus images and the variability in imaging conditions, which could affect the accuracy and reliability of the diagnostic results. Secondly, the interpretation of results generated by deep learning models may be challenging, particularly for healthcare professionals who are not familiar with artificial intelligence techniques. This could potentially lead to skepticism or mistrust in the diagnostic process. Additionally, the reliance on smartphone-based imaging may raise concerns about data privacy and security, as sensitive medical information is transmitted and stored on mobile devices.

CHAPTER 3

THEORETICAL BACKGROUND

3.1 IMPLEMENTATION ENVIRONMENT

The implementation environment to predict eye power involves the following:

Identification of Beneficiaries: The first step in the prediction of eye power is the identification of eligible places and backgrounds with proper lighting.

Eligibility Criteria: The eligibility criteria for the prediction of eye power are to have a proper phone with a medium-quality camera and stable network condition,

Overall, the implementation environment of EMP is aimed at providing free eye power checkups, but there so disadvantages to they are as follows.

- Inadequate Coverage
- Insufficient Funding
- Lack of Transparency
- Needs proper network connection

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3.2 SYSTEM ARCHITECTURE

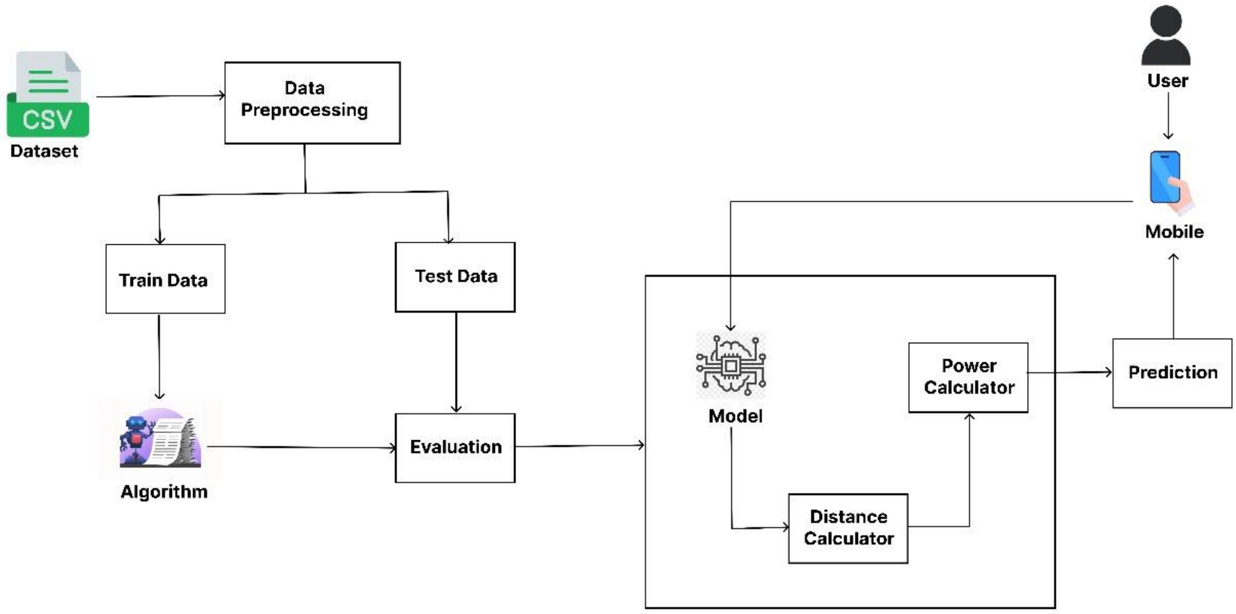

Fig 3.1. Architecture diagram of EPM

Figure 3.1 consists of the architecture of the project of EPM the user takes a picture of their face with a readable font size from the mobile device then the data is passed to a model with restful APIs, and the object detection model is used to detect eyes, then an algorithm is used to find the distance of the face from the camera, based on the given data the trained model predicts the eye power of the user with the already existing trained data.

3.3 PROPOSED METHODOLOGY

3.3.1 DATA SET DESCRIPTION

This is the dataset description. The dataset description consists of the data that we are going to train. To get the desired result. It consists of the distance and the font size. There is a sample of nearly 150 data with precise outputs. Even though the dataset is trained to get proper reports there should be some things that need to be considered they are,

- The face of the user should be clear.
- They must choose the appropriate font size.
- There should be proper lighting to take photos.

3.3.2 MODULE DESIGN

The eyes extraction model plays a crucial role in the initial stages of power prediction systems. Its primary function is to identify and isolate the eyes within an image of a person, serving as the foundational step for subsequent analysis. Once the eyes are located, the model employs advanced algorithms to extract them from the surrounding facial features. The extracted eye data serves as valuable input for various downstream tasks, particularly in power prediction systems. The extracted eye data serves as valuable input for various downstream tasks, particularly in power prediction systems. By isolating and capturing the unique characteristics of the eyes, such as pupil dilation or movement patterns, the model provides essential insights into the subject's physiological state.

Let’s say we have a marker or object with a known width *W*. We then place this marker some distance *D* from our camera. We take a picture of our object using our camera and then measure the apparent width in pixels P.

The power of the lens is calculated by measuring the object's distance from the eye and considering the average distance of image formation inside our eyes.

$$P = 1/d_i + 1/d_o$$

In which,

d_i - Image formation distance inside the eye

d_o - Object distance from the eye.

3.1 USER LOGIN TABLE

COLUMN NAME	DATA TYPE	DESCRIPTION	CONSTRAINT
USER EMAIL	VARCHAR (100)	NAME OF THE USER	NOT NULL
PASSWORD	VARCHAR (100)	USER PASSWORD	NOT NULL

Table 3.1 User Login Table

List of details used during user login which are used for authentication, so that users can be identified uniquely.

3.2 USER REGISTRATION TABLE

COLUMN NAME	DATA TYPE	DESCRIPTION	CONSTRAINT
NAME	VARCHAR (25)	NAME OF THE USER	NOT NULL
EMAIL	VARCHAR (25)	USER EMAIL	NOT NULL
PHONE NUMBER	BIGINT (20)	USER PHONE NUMBER	NOT NULL
PASSWORD	TEXT	USER ADDRESS	NOT NULL

Table 3.2 User Registration Table

User Registration details are the list of details that are stored in the database so that they can be used to identify our users and make sure that the users are not registered multiple times

3.3 MODEL PREDICTION TABLE

COLUMN NAME	DATA TYPE	DESCRIPTION	CONSTRAINT
LEFT EYE IMAGE	BIGINT (20)	USER IMAGE AS BYTES	NOT NULL
LEFT EYE FONT SIZE	INT (100)	READABLE FONT SIZE	NOT NULL
RIGHT EYE IMAGE	BIGINT (20)	USER IMAGE AS BYTES	NOT NULL
RIGHT EYE FONT SIZE	INT (100)	READABLE FONT SIZE	NOT NULL
BOTH EYES IMAGE	BIGINT (20)	USER IMAGE AS BYTES	NOT NULL
BOTH EYES FONT SIZE	INT (100)	READABLE FONT SIZE	NOT NULL

Table 3.3 Model Prediction Table

This table consists of the details that the user has to send so that the model can predict the power. The outcome of the model depends on the details provided by the user.

SOFTWARE REQUIREMENT

1. Android/ IOS OS
2. Flutter
3. Dart
4. Python
5. Django
6. Firebase
7. Vs Code

HARDWARE REQUIREMENT

1. Processor: Minimum 1 GHz
2. Memory (RAM): 4 GB
3. Camera with good resolution
4. Stable internet connection

3.3.3 MODULE DESIGN

UML DIAGRAMS

3.2 USE CASE DIAGRAM

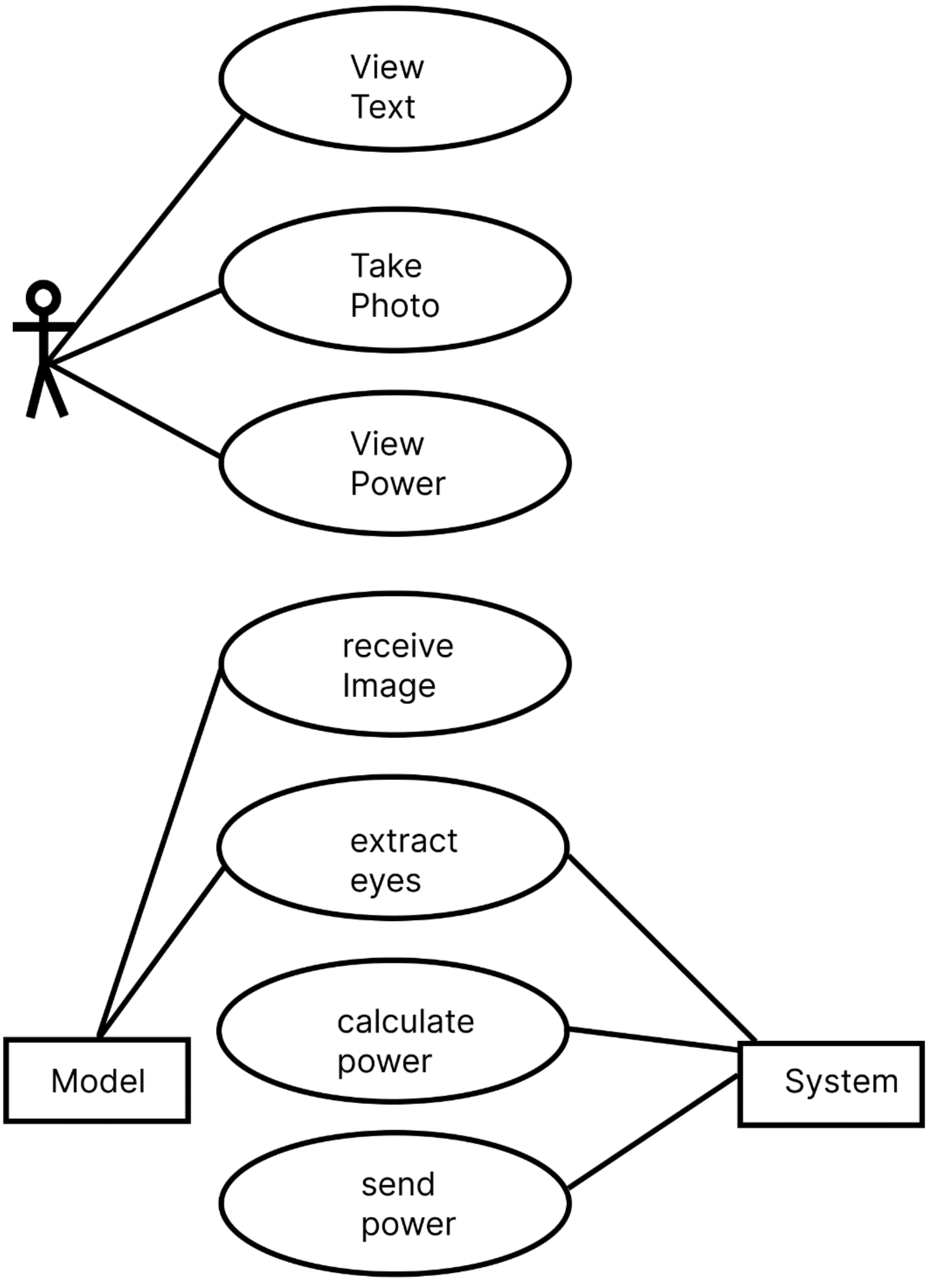

Fig 3.2 Use case diagram of EPM

This use case diagram shows all the functionalities in the EPM activities done by the user and the model and the output given by the model.

3.3 CLASS DIAGRAM

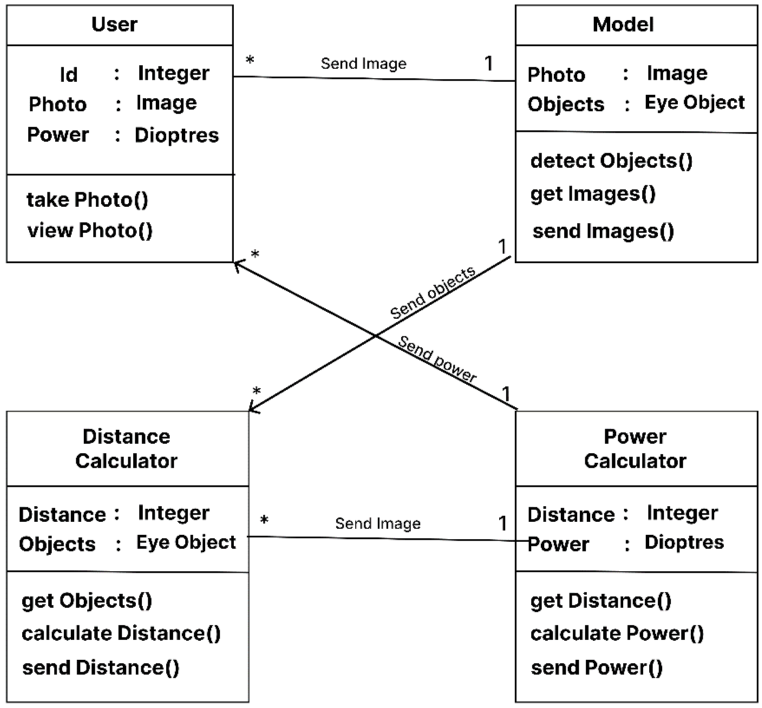

Fig 3.3 Class diagram of EPM

The above image represents the various classes used in the system. These classes play a major role in the system because they define which data has to be transferred to which module. Based on the classes we can send the data to that particular class. Data flow plays a major role when it comes to AI-based projects

3.4 SEQUENCE DIAGRAM

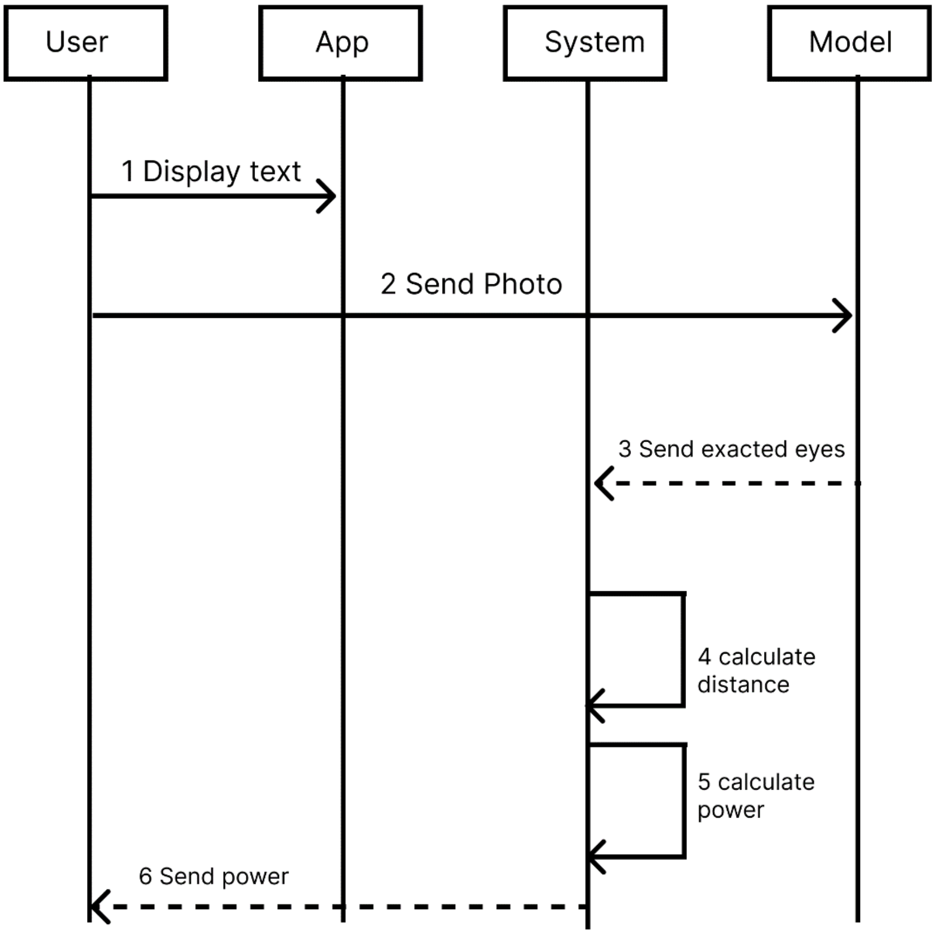

Fig 3.4 Sequence diagram of EPM

The above diagram shows the sequence of actions that are done in the process of Eye Power Prediction and each step has its significance in the process.

3.5 ACTIVITY DIAGRAM

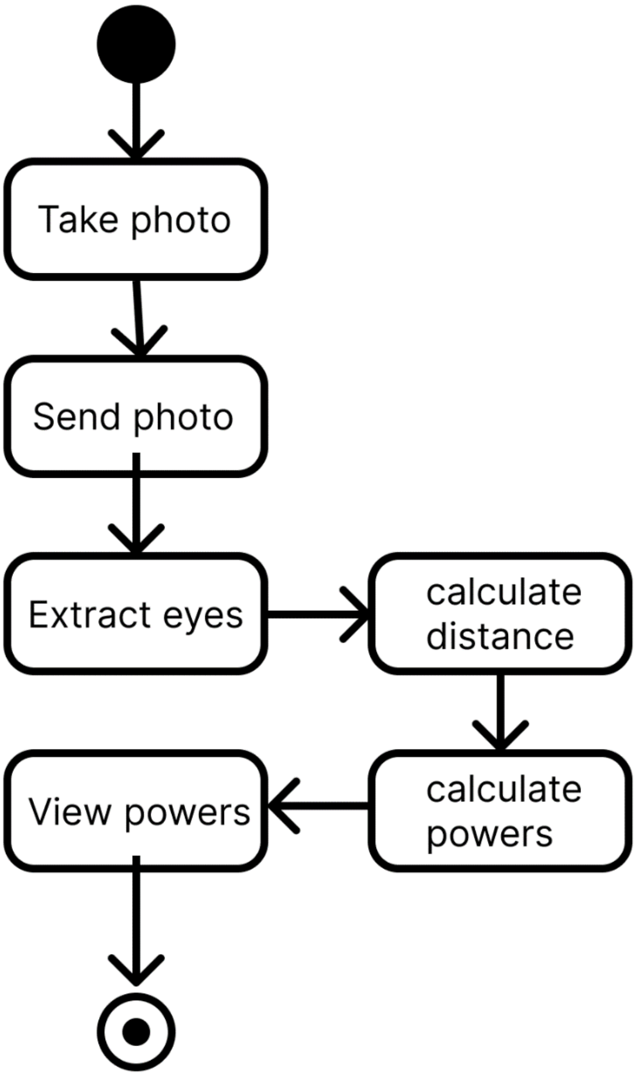

Fig 3.5 Activity diagram of EPM

The activity shows all the activities in the eye power prediction, which gives a clear explanation of the activities that are performed one after the other to achieve the final result.

3.6 COLLABORATION DIAGRAM

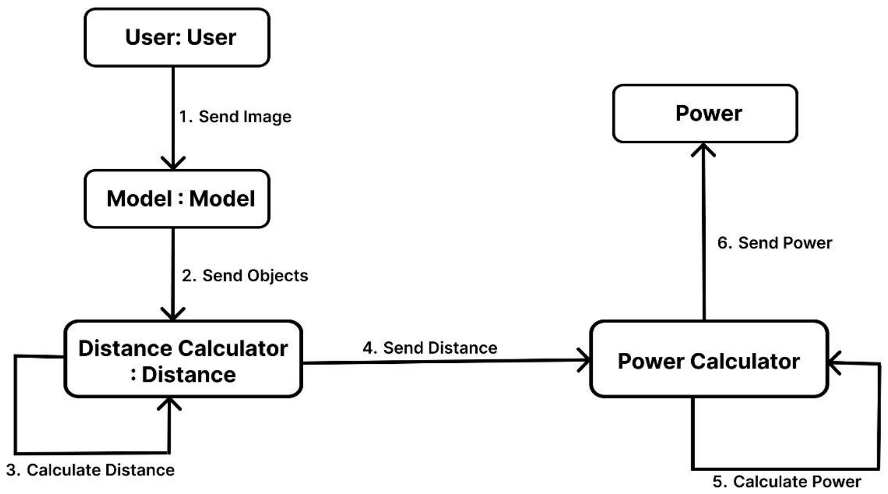

Fig 3.6 Collaboration Diagram of EPM

Figure 3.6 shows the collaboration diagram sequence of steps that are performed and the methods that are called in each step.

3.7 DEPLOYMENT DIAGRAM

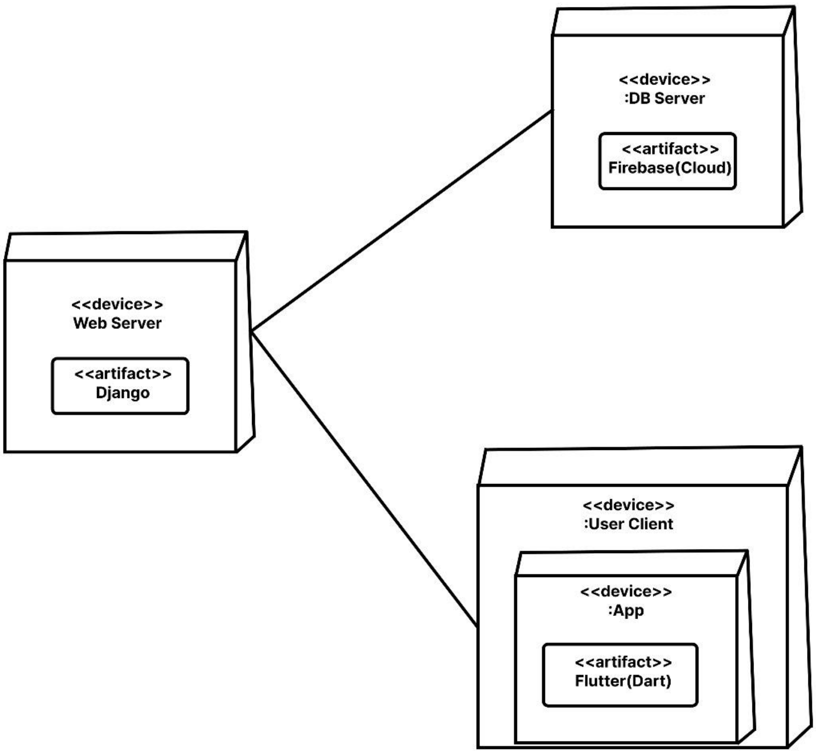

Fig 3.7 Deployment Diagram for EPM

Fig 3.7 shows the deployment architecture of the project. The model is deployed in the server which is connected with the Firebase database for login authentication and the app is connected to the server to handle the requests from the user and send them to the user.

DATA FLOW DIAGRAM

A Data Flow Diagram (DFD) is a graphical representation of the “flow” of data through an information system, modeling its aspects. It is a preliminary step used to create an overview of the system which can later be elaborated DFDs can also be used for visualization of data processing.

Level 0:

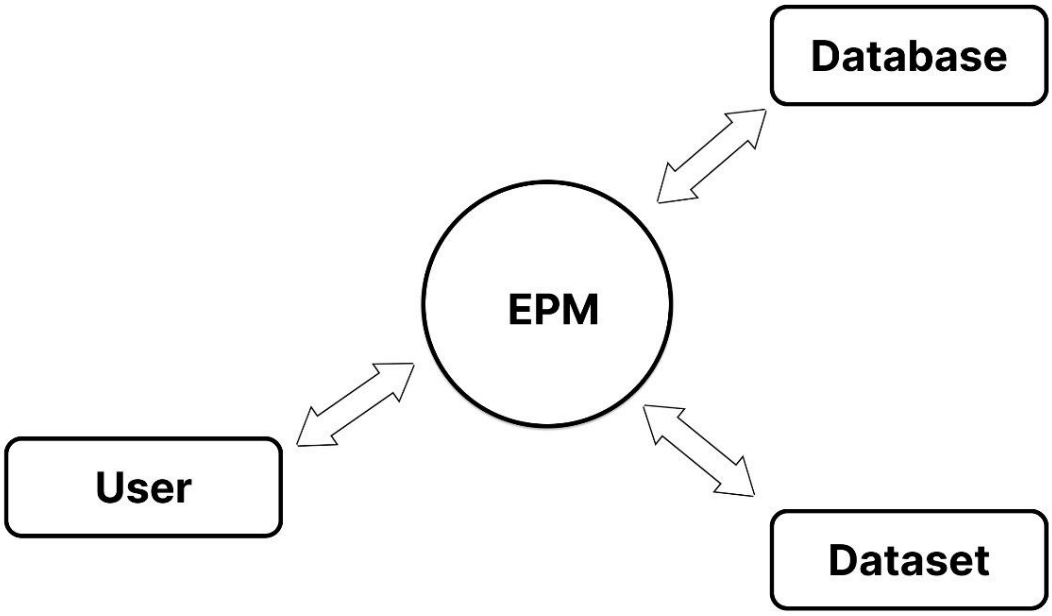

Fig 3.8 Level 0 DFD of EPM

Level 1:

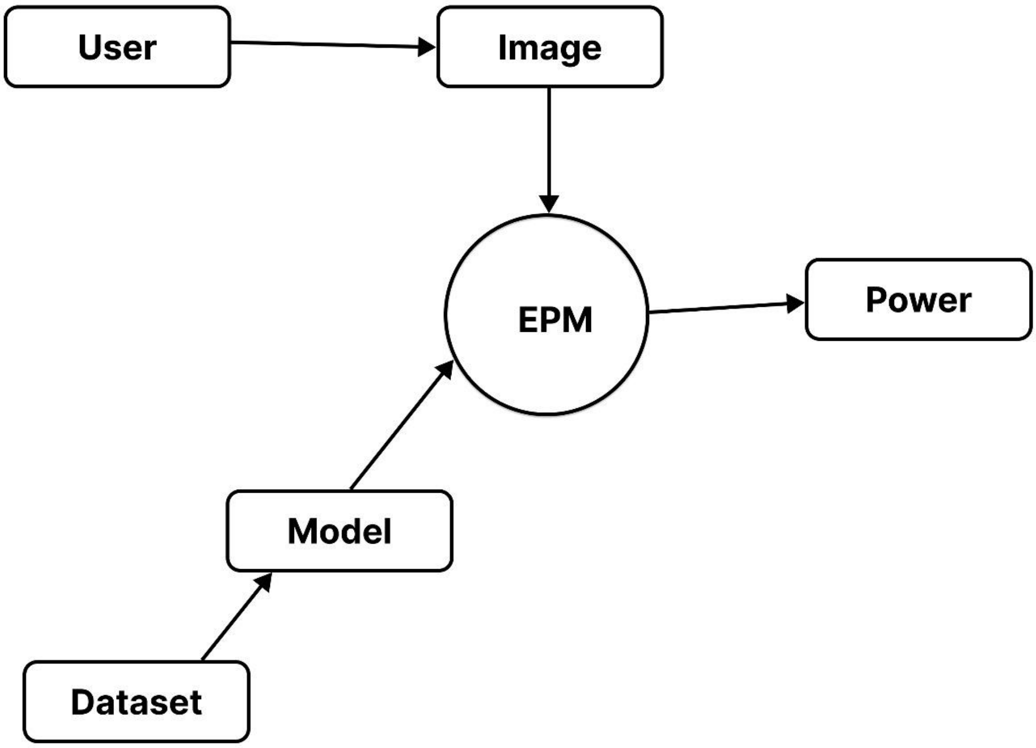

Fig 3.9 Level 1 DFD of EPM

Level 2:

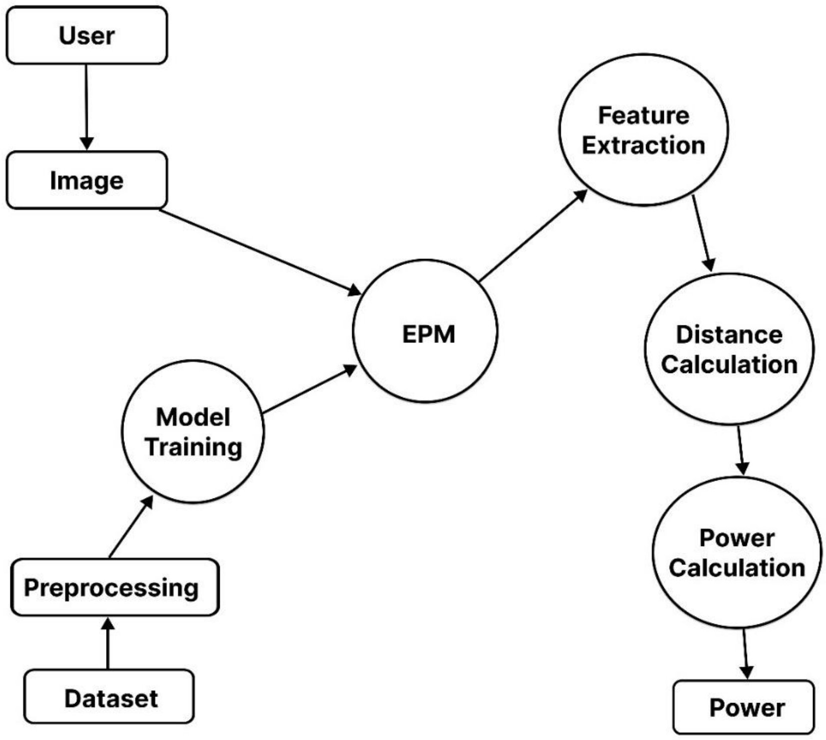

Fig 3.10 Level 2 DFD of EPM

At level 2 we can see the workflow of the model, system, and app as this works. The model gets the face of the user, and then the distance between the camera and the user's face is calculated. After finding the distance between the mobile and the user's face, the font size received from the user used with it based on the available data the eye power is measured, and the eye power is diagnosed and sent back to the user as the response.

CHAPTER 4

SYSTEM IMPLEMENTATION

EMP CONSISTS OF 7 MODULES:

- Authentication and Validation module
- User module.
- Server module
- Model Training and Evaluation module
- Feature extraction module
- Distance estimation module
- Power calculation module

4.1 AUTHENTICATION AND VERIFICATION MODULE

Authentication is done by Firebase Authentication SDK. The Firebase Authentication SDK provides methods to create and manage users who use their email addresses and passwords to sign in. Firebase Authentication also handles sending password reset emails.

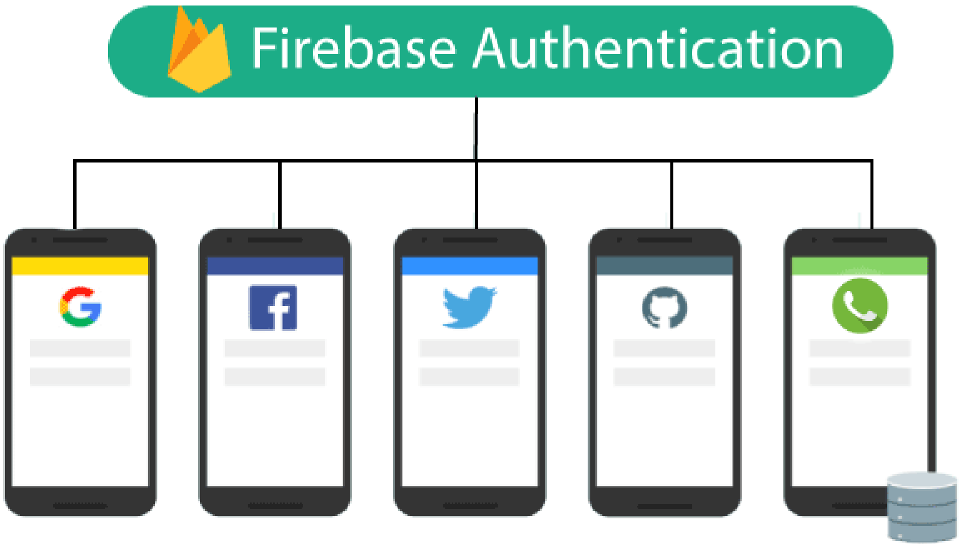

Fig. 4.1 User Authentication

4.2 USER MODULE

The user adjusts the size of the font so that it is comfortable to read, then the user is asked to take a photo while holding at a comfortable distance. Then an HTTPS request is sent to the server, after the process is completed, a response is obtained in JSON format.

Fig. 4.2 User Interface (UI)

4.3 SERVER MODULE

The system is hosted on a server so that it can be integrated with the mobile app. The image and the font size are sent to the deployed model with the help of the REST APIs with the POST method, and then the request is added to the queue when the server receives the image and the font size it proceeds to flow.

Fig. 4.3 Server

4.4 MODEL TRAINING AND EVALUATION MODULE

The dataset is collected from Kaggle. The raw dataset is preprocessed so that it can be used for model training. The processed data is used for training the model and the test dataset is used for model evaluation. After multiple evaluations and module tuning the model is saved as an exported and saved for further usage

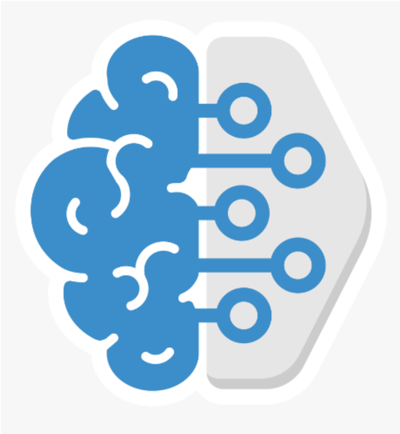

Fig. 4.4 Trained Model

4.5 FEATURE EXTRACTION MODULE

The eyes extraction model plays a crucial role in the initial stages of EPM. Its primary function is to identify and isolate the eyes within an image of a person, serving as the foundational step for subsequent analysis. Once the eyes are located, the model employs advanced algorithms to extract them from the surrounding facial features. The extracted eye data serves as valuable input for various downstream tasks, particularly in power prediction systems. By isolating and capturing the unique characteristics of the eyes, such as pupil dilation or movement patterns, the model provides essential insights into the subject's physiological state.

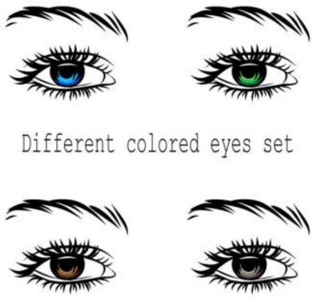

Fig. 4.5 Eye Detection

4.6 DISTANCE ESTIMATION MODULE

Let's say we have a marker or object with a known width *W*. We then place this marker some distance *D* from our camera. We take a picture of our object using our camera and then measure the apparent width in pixels *P*. This allows us to derive the perceived focal length *F* of our camera

$$F = (P * D) / W$$

By rearranging the formula, we can find the distance of the object from the camera:

$$D' = (W * F) / P$$

4.7 POWER CALCULATION MODULE

The power of the lens is calculated by measuring the object's distance from the eye and considering the average distance of image formation inside our eyes.

$P = 1/d_i + 1/d_o$

Were,

d_i - Image formation distance inside the eye

d_o - Object distance from the eye.

Fig. 4.6 Eye Power

CHAPTER 5

RESULT AND DISCUSSION

5.1 TESTING

TEST CASE ID	TESTCASE/ ACTION TO BE PERFORMED	EXPECTED RESULT	ACTUAL RESULT	PASS/ FAIL
1.	Image with proper eyes viewing at the camera	Eye Power	Calculated Eye Power	Pass
2.	Image with half-closed eyes	Eye Power	Eye Power	Pass
3.	Image with closed eyes	Error saying unable to detect	No Detection	Pass
4.	Blurry Image	Eye Power	Detected Only one Eye	Pass
5.	Unclear Image	Error	Displayed Error	Pass

Table. 5.1Test cases and Report Table for EPM

5.2 RESULT & ANALYSIS

EPM is successfully used to predict the power of the human eye which can work as an alternative to the currently used machines. As the future is moving towards AI systems, this can be an initiative for the ophthalmology department in the medical sector which deals with eye diseases. Advanced AI systems are continuously developed to increase the accuracy and success rates of medical treatments. Due to this many new inventions are adopted every year which helps doctors during the treatment of the patient. This continuous influx of technological innovations equips doctors with invaluable tools and insights, empowering them to deliver optimal treatment outcomes while navigating the complexities of ocular health conditions with greater precision and efficacy.

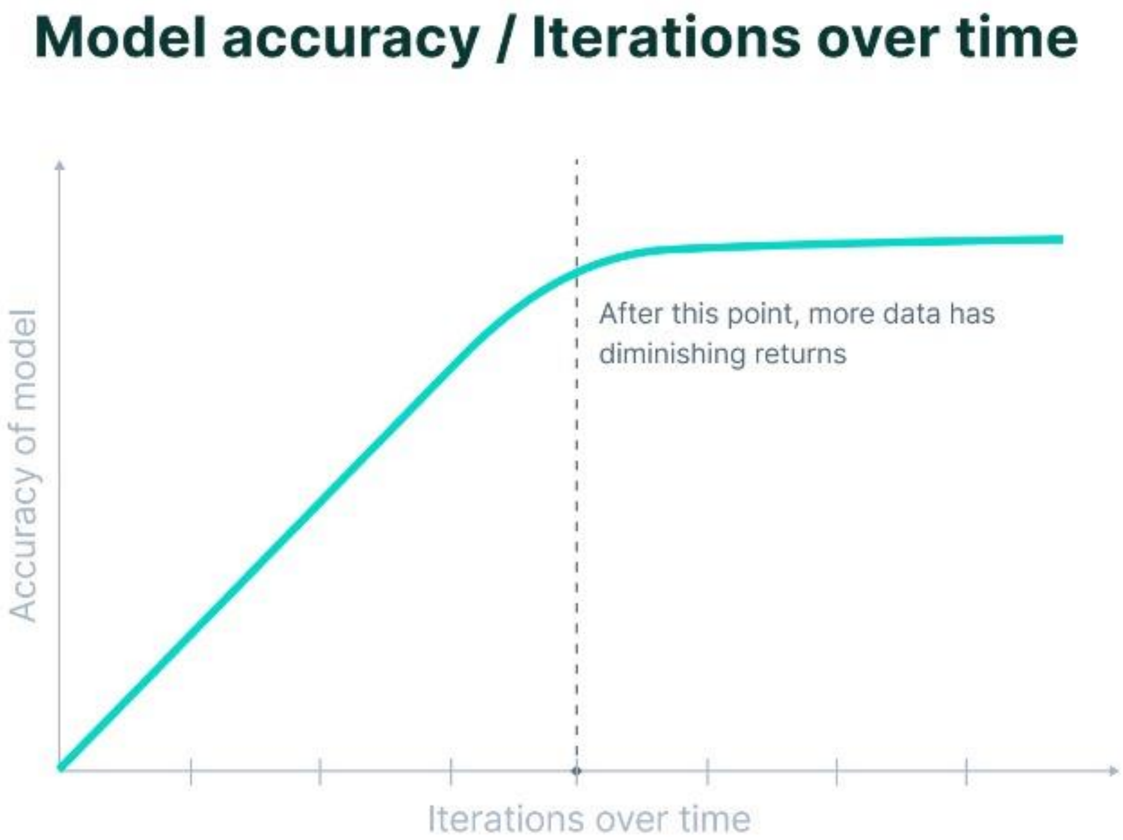

Figure 5.1 Analysis Graph

Evolution of Ophthalmic Technology: The adoption of EPM signifies a pivotal advancement in ophthalmic technology, promising a paradigm shift in the field of eye health diagnostics.

Integration of AI in Ophthalmology: The integration of EPM into AI-driven systems represents a strategic initiative within the ophthalmology department, aligning with the broader trend towards leveraging artificial intelligence for enhanced healthcare outcomes. By harnessing the power of AI, EPM stands poised to revolutionize the diagnosis and management of various eye diseases, offering unparalleled accuracy and efficiency.

Continuous Advancements in Medical Treatments: The relentless pursuit of advanced AI systems underscores a commitment to continuous improvement in medical treatments. With each passing year, new inventions and technologies emerge, designed to augment the capabilities of healthcare professionals and optimize patient care.

Enhancing Patient Care and Experience: The adoption of EPM and AI-driven technologies in ophthalmology translates into tangible benefits for patients, including more accurate diagnoses, personalized treatment plans, and improved overall healthcare experiences. By leveraging these cutting-edge tools, healthcare providers can deliver comprehensive and timely care, fostering better long-term outcomes and patient satisfaction.

5.3 DISCUSSION

Discussing the EPM involves examining its objectives, effectiveness, challenges, and potential for improvement. Here are some points to consider in a discussion about EPM:

Objectives: This discussion aims to synthesize literature on the global surge in refractive errors, explore contributing factors such as lifestyle changes and the COVID-19 pandemic, and assess the potential of deep learning-based solutions for diagnosis.

Effectiveness: This discussion seeks to evaluate the effectiveness of various factors contributing to the global surge in refractive errors, including lifestyle changes and the impact of the COVID-19 pandemic while assessing the potential efficacy of deep learning-based solutions for accurate diagnosis.

Coverage and Reach: This model and the app are completely open source so it can be used by any person and anywhere there the only requirement is to have a stable network and mobile.

Financial Inclusion: Since it's completely free and open-source people will find it very useful.

Sustainability: Ensuring the long-term sustainability of EPM requires adequate funding, strategic planning, and regular monitoring and evaluation to assess its impact and effectiveness.

Partnerships and Collaboration: Collaborating with civil society organizations, community groups, and other stakeholders can strengthen the implementation of EPM and improve its reach and impact.

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CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION:

The escalating prevalence of refractive errors poses a formidable challenge to global eye health, exacerbated by the paradigm shift induced by the COVID-19 pandemic. Addressing this challenge necessitates innovative approaches that transcend traditional diagnostic modalities. Our deep learning-based software solution, developed using OpenCV, represents a pioneering step towards democratizing access to accurate and efficient refractive error diagnosis. By harnessing the power of artificial intelligence, we aspire to mitigate the burden on healthcare systems and empower individuals to safeguard their ocular health in an increasingly digital world. Moreover, the integration of AI aligns seamlessly with the demands of an increasingly digital world, where remote healthcare services and digital health monitoring are becoming indispensable. Moving forward, continued research, development, and efforts to ensure accessibility and affordability will be key to realizing the transformative potential of AI-driven solutions in revolutionizing refractive error diagnosis and management, ultimately improving health outcomes for populations worldwide.

6.2 FUTURE ENHANCEMENTS

The future of the EPM holds opportunities for expansion, innovation, and refinement to serve the evolving needs of vulnerable populations. The model can be trained with a more high-quality dataset to precisely detect the eyes. The model can also be trained to predict the percentage of eyes closed so that that can be added as a feature to check if the user is straining to view the text.

The contents that the user views play a major role in the app. Currently, a simple text with variable size is used in the app. As the lenses with opposite power cancel out their refraction, we can do advanced image processing techniques to make the image reverse refracted. A refraction occurs when an image is viewed through a lens, and another lens with opposite power cancels out the refraction. We can create an image which is the image that is formed after it is passed through the first lens, which makes it the user with the opposite power to the refraction lens to view the image.

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APPENDICES

A.1 SDG GOALS

EPM in India contributes to several Sustainable Development Goals (SDGs) outlined by the United Nations. Here are some of the SDGs that NSAP aligns with:

GOAL 1: Good Health and Well-being: EPM supports SDG 3 by improving access to healthcare services for beneficiaries, thereby contributing to better health outcomes and overall well-being.

GOAL 2: Affordable and Clean Energy: EPM supports SDG 7 The application is open source and can be downloaded and used by anyone around the world. Since it doesn't make use of any hardware devices it is environmentally friendly and uses very less energy.

GOAL 3: Decent Work and Economic Growth: EPM aims to reduce inequalities by targeting vulnerable populations and providing them with free eye tests.

A.2 SOURCE CODE

Main.dart

```
import 'package:camera/camera.dart';
import 'package:eye_power_prediction/screens/take_picture.dart';
import 'package:flutter/material.dart';
List<CameraDescription> cameras = [];
void main() async {
  WidgetsFlutterBinding.ensureInitialized();
  cameras = await availableCameras();
  runApp(const MyApp());
}
class MyApp extends StatelessWidget {
  const MyApp({super.key});
  @override
  Widget build(BuildContext context) {
    return MaterialApp(
      title: 'Flutter Demo',
      theme: ThemeData(
        colorScheme: ColorScheme.fromSeed(seedColor: Colors.deepPurple),
        useMaterial3: true,
      ),
      debugShowCheckedModeBanner: false,
      home: const MyHomePage(title: 'Eye power predictor'),
    );
  }
}
class MyHomePage extends StatefulWidget {
  const MyHomePage({super.key, required this.title});
  final String title;
  @override
  State<MyHomePage> createState() => _MyHomePageState();
}
class _MyHomePageState extends State<MyHomePage> {
  // void _incrementCounter() {
  //   setState(() {
  //     fontSize++;
  //   });
  // }
  // void _decrimentCounter() {
  //   setState(() {
  //     fontSize--;
  //   });
  // }

  // double fontSize = 30;

  @override
  Widget build(BuildContext context) {
    return Scaffold(
      appBar: AppBar(
```

```
      centerTitle: true,
      backgroundColor: Theme.of(context).colorScheme.inversePrimary,
      title: Text(widget.title),
    ),
    body: SingleChildScrollView(
      child: Column(
        children: <Widget>[
          const Padding(
            padding: EdgeInsets.all(25.0),
            child: Text(
              'To predict the eye power please hold the phone away from your face, then try to increase the
size of the size of the font using the buttons bellow. when you feel it hard to read the text please click the
camera button and take a selfi of your face with proper lighting and procceed to predict your eye power.',
              textAlign: TextAlign.center,
              style: TextStyle(fontSize: 20),
            ),
          ),
          // Padding(
          //   padding: const EdgeInsets.all(20.0),
          //   child: Text(
          //     "Hi I'm your virtual eye doctor!!",
          //     textAlign: TextAlign.center,
          //     style:
          //         TextStyle(fontWeight: FontWeight.bold, fontSize: fontSize),
          //   ),
          // ),
          // const SizedBox(
          //   height: 20,
          // ),
          // Row(
          //   mainAxisAlignment: MainAxisAlignment.spaceEvenly,
          //   children: [
          //     FloatingActionButton(
          //       onPressed: _decrimentCounter,
          //       heroTag: "btn_1",
          //       tooltip: 'reduce',
          //       child: const Icon(Icons.remove),
          //     ),
          //     FloatingActionButton(
          //       heroTag: "btn_2",
          //       onPressed: _incrementCounter,
          //       tooltip: 'Increment',
          //       child: const Icon(Icons.add),
          //     ),
          //   ],
          // )
        ],
      ),
    ),
    floatingActionButton: FloatingActionButton(
      heroTag: "btn_3",
      onPressed: () {
```

```
        int idx = cameras.indexWhere(
            (element) => element.lensDirection == CameraLensDirection.front);
        if (idx == -1) {
          idx = 0;
        }
        Navigator.push(
            context,
            MaterialPageRoute(
                builder: (context) =>
                    TakePictureScreen(fontSize: 0, camera: cameras[idx])));
      },
      tooltip: 'Increment',
      child: const Icon(Icons.camera_alt),
    ),
  );
 }
}
```

OutputScreen.dart

```
import 'package:flutter/material.dart';

class OutputScreen extends StatefulWidget {
  const OutputScreen(
      {super.key, required this.imagePath, required this.fontSize});
  final String imagePath;
  final double fontSize;

  @override
  State<OutputScreen> createState() => _OutputScreenState();
}

class _OutputScreenState extends State<OutputScreen> {
  @override
  void initState() {
    super.initState();
    loadData();
  }

  bool isLoading = true;
  loadData() {
    Future.delayed(const Duration(seconds: 4), () {
      isLoading = false;
      setState(() {});
    });
  }

  @override
  Widget build(BuildContext context) {
    return Scaffold(
      body: isLoading
          ? const Center(
```

```
        child: Column(
          mainAxisAlignment: MainAxisAlignment.center,
          children: [
            SizedBox(
              height: 100,
              width: 100,
              child: CircularProgressIndicator(
                strokeWidth: 20,
              ),
            ),
            SizedBox(
              height: 20,
            ),
            Text(
              "Please wait while we analyse your data",
              textAlign: TextAlign.center,
              style: TextStyle(fontWeight: FontWeight.bold, fontSize: 25),
            )
          ],
        ),
      )
    : const Center(
        child: Column(
          mainAxisAlignment: MainAxisAlignment.center,
          children: [
            Icon(
              Icons.remove_red_eye_outlined,
              size: 100,
            ),
            SizedBox(
              height: 20,
            ),
            Column(
              crossAxisAlignment: CrossAxisAlignment.start,
              children: [
                Text(
                  "Here is your report.",
                  textAlign: TextAlign.center,
                  style: TextStyle(
                      fontWeight: FontWeight.bold, fontSize: 25),
                ),
                SizedBox(
                  height: 10,
                ),
                Text("Left eye: ---",
                    style: TextStyle(
                        fontWeight: FontWeight.bold, fontSize: 20)),
                Text("right eye: ---",
                    style: TextStyle(
                        fontWeight: FontWeight.bold, fontSize: 20)),
                Text("you might have: ---",
                    style: TextStyle(
```

```
                    fontWeight: FontWeight.bold, fontSize: 20)),
              ],
            )
          ],
        ),
      ),
    );
  }
}
```

VerificationScreen.dart

```
import 'dart:io';

import 'package:eye_power_prediction/screens/output_screen.dart';
import 'package:flutter/material.dart';

class ProceedScreen extends StatelessWidget {
  final String imagePath;
  final double fontSize;

  const ProceedScreen(
      {super.key, required this.imagePath, required this.fontSize});

  @override
  Widget build(BuildContext context) {
    return Scaffold(
      appBar: AppBar(title: const Text('Preview')),
      body: Column(
        crossAxisAlignment: CrossAxisAlignment.start,
        children: [
          Image.file(File(imagePath)),
          const SizedBox(
            height: 25,
          ),
          Text(
            "Fontsize: $fontSize",
            style: const TextStyle(fontSize: 25, fontWeight: FontWeight.bold),
          )
        ],
      ),
      floatingActionButton: FloatingActionButton(
        onPressed: () async {
          Navigator.of(context).push(
            MaterialPageRoute(
              builder: (context) => OutputScreen(
                fontSize: fontSize,
                imagePath: imagePath,
              ),
            ),
          );
```

```
        },
        child: const Icon(Icons.arrow_forward_outlined),
      ),
    );
  }
}
```

CaptureImage.dart

```
import 'dart:async';

import 'package:camera/camera.dart';
import 'package:eye_power_prediction/screens/proceed_screen.dart';
import 'package:flutter/material.dart';

class TakePictureScreen extends StatefulWidget {
  const TakePictureScreen({
    super.key,
    required this.camera,
    required this.fontSize,
  });

  final CameraDescription camera;
  final double fontSize;

  @override
  TakePictureScreenState createState() => TakePictureScreenState();
}

class TakePictureScreenState extends State<TakePictureScreen> {
  late CameraController _controller;
  late Future<void> _initializeControllerFuture;

  @override
  void initState() {
    super.initState();

    _controller = CameraController(
      widget.camera,
      ResolutionPreset.medium,
    );

    _initializeControllerFuture = _controller.initialize();
  }

  @override
  void dispose() {
    _controller.dispose();
    super.dispose();
  }

  void _incrementCounter() {
```

```
  setState(() {
    fontSize++;
  });
}

void _decrimentCounter() {
  setState(() {
    fontSize--;
  });
}

double fontSize = 30;

@override
Widget build(BuildContext context) {
  return Scaffold(
    appBar: AppBar(title: const Text('Take a picture')),
    body: Stack(
      children: [
        FutureBuilder<void>(
          future: _initializeControllerFuture,
          builder: (context, snapshot) {
            if (snapshot.connectionState == ConnectionState.done) {
              return CameraPreview(_controller);
            } else {
              return const Center(child: CircularProgressIndicator());
            }
          },
        ),
        Positioned(
          left: 0,
          right: 0,
          top: 25,
          child: Text(
            "Hi I'm your virtual eye doctor!!",
            textAlign: TextAlign.center,
            style: TextStyle(
                backgroundColor: Colors.white,
                fontWeight: FontWeight.bold,
                fontSize: fontSize),
          ),
        ),
      ],
    ),
    bottomNavigationBar: Padding(
      padding: const EdgeInsets.all(8.0),
      child: Row(
        mainAxisAlignment: MainAxisAlignment.spaceEvenly,
        children: [
          FloatingActionButton(
            onPressed: _decrimentCounter,
            heroTag: "btn_1",
```

```
          tooltip: 'reduce',
          child: const Icon(Icons.remove),
        ),
        FloatingActionButton(
          heroTag: "btn_2",
          onPressed: _incrementCounter,
          tooltip: 'Increment',
          child: const Icon(Icons.add),
        ),
        FloatingActionButton(
          onPressed: () async {
            try {
              await _initializeControllerFuture;

              final image = await _controller.takePicture();

              if (!context.mounted) return;

              await Navigator.of(context).push(
                MaterialPageRoute(
                  builder: (context) => ProceedScreen(
                    fontSize: fontSize,
                    imagePath: image.path,
                  ),
                ),
              );
            } catch (e) {
              print(e);
            }
          },
          child: const Icon(Icons.camera_alt),
        )
      ],
    ),
  ),
 );
 }
}
```

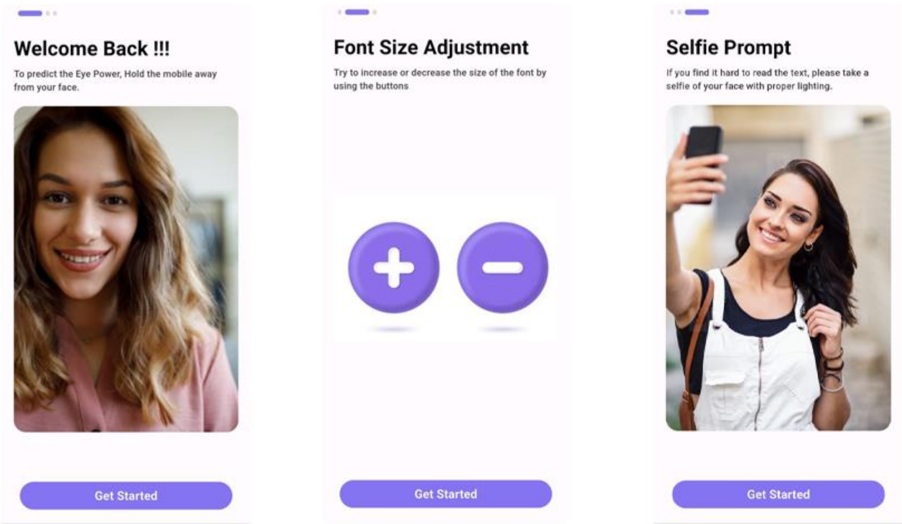
API.py

```
from rest_framework.views import APIView
import cv2
from rest_framework.response import Response
import numpy as np
import urllib.request
from .serializers import DataModelSerializer
from rest_framework import status

class PredictPower(APIView):
    def post(self, request):
        try:
```

```
    # Parse incoming data from request
  data = request.data

  # Deserialize and validate data using serializer
  serializer = DataModelSerializer(data=data)
  if serializer.is_valid():
  # Save validated data to database
    serializer.save()
    # fontsize=request.data['fontSize']
    # Load the pre-trained Haar cascade classifier for eye detection
    xml_path = 'myapp/haarcascade_eye.xml'
    eye_cascade = cv2.CascadeClassifier(xml_path)

    # Camera parameters for distance estimation (in real-world units)
    focal_length = 800  # Focal length of the camera in pixels (example value)
    average_eye_size = 30  # Average size of an eye in pixels (example value)
    url =request.data['image']

    # Download the image from the URL
    req = urllib.request.urlopen(url)
    arr = np.asarray(bytearray(req.read()), dtype=np.uint8)

    # Decode the image data
    img = cv2.imdecode(arr, -1)
    # Load the image
    cv2.imwrite('testing_image.jpg', img)

# Read the downloaded image
    image = cv2.imread('testing_image.jpg')

    # Convert the image to grayscale for better processing
    gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

    # Detect eyes in the image
    eyes = eye_cascade.detectMultiScale(gray, scaleFactor=1.1, minNeighbors=5)
    totaldistance = 0
    # Draw rectangles around detected eyes and estimate distance
    for (ex, ey, ew, eh) in eyes:
      # Calculate distance to the eye using monocular depth estimation
      # Depth = (average_eye_size * focal_length) / eye_size_in_pixels
      distance = (average_eye_size * focal_length) / ew
      distance = round(distance, 2) / 100  # Round to two decimal places
      totaldistance += distance
    totaldistance = totaldistance / 2
    pupildis = 0.03
    distantpower = (1 / pupildis)
    closepower = (1 / totaldistance) + (1 / pupildis)
    power = (1 / closepower) + (1 / distantpower)
    return Response({"power": power})
  else:
  # Return error response if data is invalid
    return Response(serializer.errors, status=status.HTTP_400_BAD_REQUEST)
```

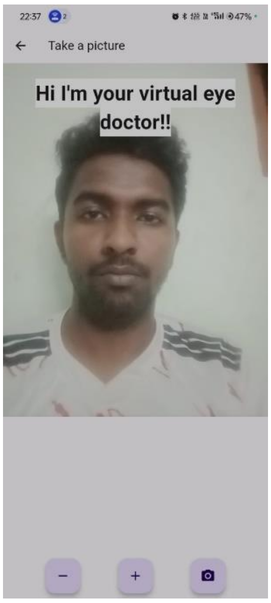
```
except Exception as e:
    return Response({"error":str(e)}, status=500)
```

A.3 SCREEN SHOT



A.3.1 Home Screen

This the intro page of the app which tells the instruction and the usage of the app.



A.3.2 Image Capturing Screen

This is the image capturing page of the app from here we see the font size and take picture.

This is the output page of the app which predicts and tell the power of eye sight.

A.3.3 Image Verification Screen

This is the preview screen before we procced to next page.

A.3.4 Output Screen

This is the output page of the app which predicts and tell the power of eye sight.

A.4 PLAGIARISM REPORT

Eye Power Prediction Using Deep Learning

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Abstract*-Refractive errors have become a global issue. There has been a huge increase in system and mobile usage after the pandemic COVID -19. During the pandemic due to online classes, the average screen time of people has increased, which is a major cause of the increase in refractive error disease. Currently, autorefractor is used to find and measure the refractive errors. We have developed software that can be used to find the refractive errors

Keywords—Myopia, Hyperopia, Refraction.

I. INTRODUCTION

A. Refractive Errors

Refractive errors are a type of visual problem that reduces our visibility and makes it hard to see. The image is formed at the retina of the eye for a normal eye, which is real and inverted. If the image is formed before or beyond the retina then it is called a refractive error. These are caused by many reasons such as increasing or decreasing the length of the eyeball, the cornea (the outer layer of the eye) is not in shape, and due to aging also the human eye lens becomes thinner. The various that are currently known are far-sightedness (hyperopia), near-sightedness (myopia), presbyopia, and astigmatism.

Refractive errors are corrected in many ways. Some wear spectacles with a lens fixed inside the spectacles with a specific power so that the person can see clearly. Another method is wearing contact lenses with a specific power. Lenses are costly when compared to spectacles. Both these solutions are a temporary solution that helps people see clearly in their day-to-day lives. Another solution is surgery which allows the user to see clearly without the use of any spectacles or contact lenses

B. Eye Power

The near point is the closest distance that an image can be viewed, such that it forms a clear image on the retina. Similarly, the far point is the distance an object is visible to the naked eye. A normal person's vision can view objects placed at a distance ranging from 25cm to infinity. Here, we can consider the near point as 20cm. Power can be calculated as

$$P = 1/f$$

Where f represents the focal length given in meters. With the focal length given in meters, the unit of Power is dioptres(D). The focal length can be calculated with the normal lens focal length calculation which gives us the power equation as

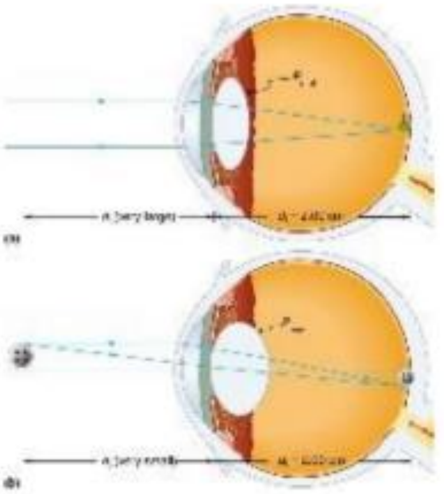
$$P = 1/d_o + 1/d_i$$

Where,

d_o is the distance of the object from the eye and d_i is the image distance from the eye lens.

For objects at infinity, the distance is considered as infinity and can be neglected from the equation since division by infinity is 0. So, the equation becomes,

$$P = 1/d_i$$



[figure-3.1 – Object Distance and Image Formation on the Retina]

A. LITERATURE SURVEY

Holden, B. A., and et.al [1] proposed a comprehensive meta-analysis documenting the global prevalence of myopia and high myopia, projecting significant increases through 2050.

Wu, P. C., and et.al [2] proposed a longitudinal study highlighting how outdoor activities impact the refractive status and myopia progression in school children.

Rose, K. A., and et.al [3] proposed that they explore the association between myopia and lifestyle factors among students of Chinese ethnicity in Singapore and Sydney.

Verhoeven, V. J., and et.al [4] proposed conducting genome-wide meta-analyses identifying multiple susceptibility loci for refractive error and myopia, elucidating the genetic underpinnings of these conditions.

Mojumder, D., and et.al [5] discussed the implications of the COVID-19 era on refractive errors, highlighting the exacerbation of ocular health challenges due to prolonged screen time and lifestyle changes.

Li, X., Zhang, and et.al [6] proposed a deep learning approach for high-quality single-shot HDR imaging, demonstrating its potential for enhancing refractive error diagnosis. Leveraging

Chang and Manning [6] developed innovative methodologies for refractive error assessment, showcasing the efficacy of deep learning-based software solutions in this domain.

Saw, S.M., Gazzard, and et.al [7] researched myopia, the epidemiology of myopia, its associated risk factors, and potential pathological complications. Understanding these complications plays a major role in creating management and prevention strategies.

Dirani, M., and et.al [8] found out that the risk of myopia reduces with an increase in time spent outdoors, highlighting the potential importance of outdoor activities in myopia prevention strategies.

Morgan, I. G., and et.al [9] explored the complex interplay of genetic, environmental, and lifestyle factors contributing to the myopia epidemic. Additionally, it discusses potential interventions and prevention strategies, such as outdoor activities, optical interventions, and pharmaceutical approaches, aimed at curbing the progression of myopia and its associated complications.

Xiong, S., Sankaridurg, and et.al [10] evaluated how time spent outdoors impacts myopia. They suggest that the risk of myopia is reduced with increased outdoor activity and it helps in the progression of providing valuable insights for public health interventions aimed at tackling the myopia epidemic.

B. PROPOSED SYSTEM

The most vital thing needed for any prediction is the dataset that has to be used for training the model and using this trained model the prediction is done by custom inputs.

1. Data Collection

The dataset is collected from Kaggle which is used to train our model. The dataset contains images of human faces along with the human eyes marked as bounding boxes with the required data which allows our model to predict the features from the model to identify human eyes.

2. Data Preprocessing and Preparation

Before training the model, the dataset has to be analyzed and preprocessed so that the model can be trained easily. All the images are analyzed and the list of classes that are mentioned in the images are identified. Some images may contain many classes. The list of classes is analyzed and the required classes are sorted out omitting the unwanted classes. From the new list of classes, the images are split so that unwanted classes are removed. Unwanted classes may create interruptions while detecting the necessary objects. Some of the major issues are like if we want to count the number of classes in the image and the model detects unnecessary or unwanted classes then it'll lead to errors in the final result. So, the dataset has to be processed properly before training the model

After preprocessing the dataset has to be prepared accordingly for model training. The dataset is processed and a good well-structured dataset is obtained such that the model can be trained to get highly accurate results.

[figure-3.2 – Result of eyes extraction model]

3. Eyes Extraction Module

The eyes extraction model's primary function is to extract features (i.e., eyes) from the image of a person, serving as the foundational step for subsequent analysis. Once the eyes are located, the model employs advanced algorithms to extract them from the surrounding facial features. The extracted eye data serves as valuable input for various downstream tasks, particularly in power prediction systems. By isolating and capturing the unique characteristics of the eyes, such as pupil dilation or movement patterns, the model provides essential insights into the subject's physiological state.

4. Distance Estimation Module

Assume that we have an object or marker with a width W. The marker is then positioned D away from our camera. After utilizing our camera to capture an image of our item, we calculate the apparent width in pixels P. This enables us to determine our camera's apparent focal length, F.

$$F = (P * D) / W$$

By rearranging the formula, we can find the distance of the object from the camera:

$$D' = (W * F) / P$$

5. Power Calculation Module

The power of the lens is calculated by measuring the distance of the object from the eye and considering the average distance of image formation inside our eyes.

$$P = 1/d_i + 1/d_o$$

Where,

d_i - Image formation distance inside the eye

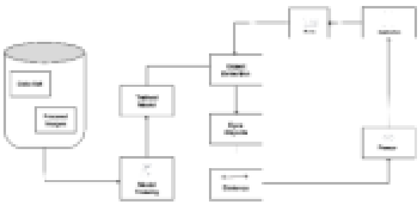
d_o - Object distance from the eye.

Where:

P - lens power in dioptres(D)
F - lens's focal length in meters (m)

d_o & d_i – object distance, and image formation distance in meters respectively.

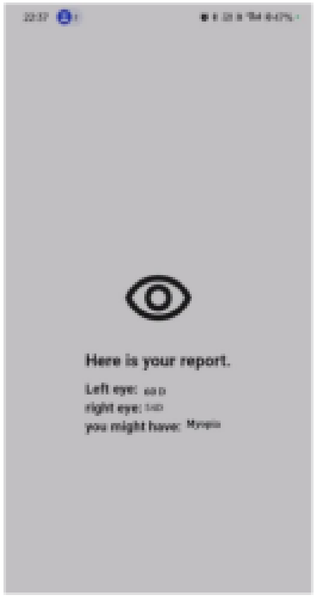
Unlike artificial lenses, the human eye's lens is a biological structure with a certain range of flexibilities. This flexibility allows humans to focus and this process is called accommodation. For an average, the focal length for a relaxed eye is 17mm. But what's so important is the vision correction which allows us to focus on the content clearly



[figure-3.3 – Architecture]

C. CONCLUSION

The escalating prevalence of refractive errors poses a formidable challenge to global eye health, exacerbated by the paradigm shift induced by the COVID-19 pandemic. Addressing this challenge necessitates innovative approaches that transcend traditional diagnostic modalities. Our deep learning-based software solution, developed using OpenCV, represents a pioneering step towards democratizing access to accurate and efficient refractive error diagnosis. By harnessing the power of artificial intelligence, we aspire to mitigate the burden on healthcare systems and empower individuals to safeguard their ocular health in an increasingly digital world. Moreover, the integration of AI aligns seamlessly with the demands of an increasingly digital world, where remote healthcare services and digital health monitoring are becoming indispensable. Moving forward, continued research, development, and efforts to ensure accessibility and affordability will be key to realizing the transformative potential of AI-driven solutions in revolutionizing refractive error diagnosis and management, ultimately improving health outcomes for populations worldwide.



[figure-3.3 – Output Screen]

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