UNIFIED INTELLIGENCE IN OPHTHALMOLOGY: A COMPREHENSIVE REVIEW OF A SINGLE FRAMEWORK FOR PREDICTING MULTIPLE EYE DISEASES

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Abstract

Diabetic ocular disorders are among the most important public health concerns, affecting millions of people with severe degrees of visual loss worldwide. Mild, non-blinding conditions and severe complications, such as diabetic retinopathy, diabetic macular edema, glaucoma, and cataracts, often appear due to uncontrolled diabetes. Presently, more than 145 million people worldwide are diagnosed with the raging global diabetes epidemic, and this number is estimated to increase further. Thus, early detection and prompt intervention play an important role in preventing vision damage. Earlier diagnostic systems faced a major drawback, as the framework was unable to handle different types of data. This restriction limited their capability in systematic multiple eye disease [MED] detection, particularly in clinical settings where diagnosis is a procedural task and where data is multi-sourced, such as clinical records, fundus-captured photos, and OCT exam information. This review discusses the development of a single AI framework that can handle structural and unstructured datasets to identify different stages of MED. It is termed as MED as it deals with multiple diseases such as diabetic retinopathy, diabetic macular edema, glaucoma, and cataracts. This survey also describes the developmental stages of segmentation techniques and also highlights the advanced techniques such as U-Net and SegFormer, which can be effectively used for anatomical segmentation, which is used in disease identification for both optical coherence tomography (OCT) and fundus datasets. Furthermore, it helps in understanding the workflow for developing an effective MED framework.

Key words

Multiple eye disease, Artificial Intelligence in Ophthalmology, U-Net, Data Privacy in Ophthalmology.

1 Introduction

Artificial intelligence (AI) and machine learning have been an explosive impact in the field of ophthalmology and have resulted in significant advancements in the diagnosis and treatment of several ocular diseases such as diabetic retinopathy, age-related macular degeneration, glaucomatous optic neuropathy, and cataracts. Traditional diagnostic models are based on single diseases, are highly specific, and are often unworkable when information is scant or where large amounts of data are needed to exclude other potential conditions [He et al., 2021]. AI tools have shown great promise in aiding in these diagnostic roles using structured clinical data (eg., blood glucose, cholesterol, age) and unstructured image data (e.g. fundus photographs, OCT scans).

This review presents a conceptual single AI framework capable of diagnosing multiple eye diseases (MED) across their entire clinical spectrum without the necessity for direct integration of image and clinical data. Rather, the framework leverages modular branches enabling independent processing of structured and unstructured data under a common diagnostic workflow. This review aids in developing a unified framework capable of handling multiple modalities for effective forecasting of MED, from early detection to advanced stages. The article explores strategies for building a unified framework that leverages recent advances in artificial intelligence to address the challenges of diagnosing MED. The integration of many imaging modalities and clinical data presents a considerable obstacle in the development of MED models. The imaging modalities include Optical Coherence Tomography (OCT), fundus photography, and clinical datasets—each capable of serving as the ideal diagnostic tool for specific ocular conditions.

Effectively using multiple modalities within a singular AI framework can help build an efficient diagnostic tool capable of managing any stage of MED [Mateen et al., 2020]. This research examines the current state of MED platforms and their incorporation of various data sources to analyze contemporary MED models inside a centralized forecasting center, while evaluating the benefits and challenges of developing a fully integrated, data-driven framework.

Segmentation methods are used in various stages of the MED prediction process for anatomical analysis to find different parts in medical images. From simple methods like thresholding and region-growing, it has come a long way to more advanced deep-learning techniques including Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), U-Net, to transformer-based approaches like SegFormer. Feature detection is now much more accurate, and tools can now process images to detect features that previously caused bottlenecks in diagnostic workflows. Segmentation techniques in medical image analysis have progressed significantly, transforming how MED can be predicted. Standard techniques, such as thresholding and region growing, provide the necessary tools for anatomical examination, but they often struggle with complex structures and variability in image quality [Piorkowski et al., 2017] Deep learning has provided an entirely new life to segmentation tasks by reducing error rates. CNNs introduced the automatic learning of hierarchical features, and FCNs enabled end-to-end training for pixel-wise predictions. The contracting and expanding paths of U-Net architecture have made it a staple in medical image segmentation, excelling in capturing both local and global contexts. The major hurdles in this field and proposes a systematic method has been listed below.

• Multi-modality such of OCT, fundus images, and clinical data within can be used to improves the prognosis and diagnosis of MED.

• Efficient model to build MED also involves several techniques in each phase of its workflow therefore a clear understanding of these technique for image and clinical data is required.

• The accuracy of MED classification can be enhanced through the evolution of segmentation techniques from traditional methods to modern deep-learning models.

• Real-world clinical validation and generalisability of AI models for MED while balancing ethical compliance and effectiveness across heterogeneous datasets

The review helps in building a data-driven framework for MED detection which focuses on four key areas: Comparative and Comprehensive Study, detailed technical workflow for effective MED detection, History and Evolution of Segmentation Techniques, and understanding Performance Evaluation, and gives a unified idea in understanding the ethical considerations and approach for real-world testing. It details how clinical data and image data can be used in building a data-driven framework for MED that can help ophthalmologists to use it as an aid to diagnose any stage of the disease.

2 Literature Survey

Muthukannan et al. [Muthukannan2022] proposed CNN-MDD, which denotes Convolutional Neural Networks for Multi-Disease Diagnosis, as a high-performance, deep learning model specifically tailored for the ODIR data set. Their model was one among the high performances performed continuously outperforming various optimized models with significant margins along various criteria. The model realized very high precision at 98.30%, accuracy at 95.27%, specificity at 95.21%, and recall at 93.3%, therefore validating the CNN-MDD technique in the detection of various ocular illnesses. It represented a significant step toward automated diagnosis of ocular diseases and was expected to be clinically precise.

Shamsan et al. [Shamsan et al., 2023] proposed a model in which they classify a large number of eye diseases using feature extraction as well as fusion techniques. This technique utilises ANN along with PCA to reduce features produced from the classification model based on MobileNet and DenseNet121 models created for this dataset of eye disorders. The second approach combines feature from both MobileNet and DenseNet121 models. These are used either before or after dimensionality reduction to classify images of eye disorders. In the third approach, handcrafted features from the MobileNet and DenseNet121 models were combined with an ANN for the classification of the eye disease dataset. The images in the dataset were sourced from Ocular Recognition, the Indian Diabetic Retinopathy Image Collection (IDRiD), and High-Resolution Fundus.

Bowmik et al. [Bhowmik et al., 2019] designed a model for detecting age-related eye diseases based on pretrained VGG16 and Inception V3 models. The model was trained on 84,495 images from an OCT device in the Kaggle database, achieving accuracies of 94% for the test data and 99.94% for the training data.

Using eye movement analysis and a machine learning-based approach, Hammoud et al. [Hammoud et al.,2023] have developed a novel approach for the early diagnosis of Parkinson's disease (PD) and Progressive Supranuclear Palsy (PSP). The team used a deep learning system to extract features from pupil images, which they then visualized using a technique known as time-series imaging. These images were fed into the model of disease detection to determine whether the subject had PD, PSP, or neither. Interestingly, the maximum performance of the model occurred when the subject was undergoing optokinetic activity, an eye movement test.

Nazir et al. [Nazir et al.,2020] proposed a model which integrated Fuzzy K-means (FKM) clustering and the Fast Region-based Convolution Neural Network (FRCNN) approach. According to the authors, the model was designed for the automatic detection and diagnosis of diabetes-related ocular pathologies such as DR, DME, and glaucoma. The methodology was divided into two major stages, which incorporated eye disease identification and the use of FKM clustering in localizing and segmenting the affected regions. The FRCNN approach significantly improves the segmentation performance and shows a stronger capability in extracting deep feature images for optimal representations of ocular problems. On average, the Intersection over Union (IoU) was 0.95, and the mean average.

Malik et al. [Malik et al.,2019] proposed a unified framework to record diagnostic data in an internationally standardized format to enable the disease diagnosis and prediction using machine learning algorithms, focusing on hierarchical data organization to enhance machine readability and precise analysis by machine learning models. Among these algorithms are decision trees, random forests, Naive Bayes, and even neural networks. With this, performance across these algorithms can be compared and the best method selected for each dataset. Additionally, the framework allows more emphasis on self-learning and its ability to come up with unique classifications of diagnoses and symptoms.

Table 1. Summary of MED with Limitation Inference

Ref No	Scope	Model Used	Modality	Data Size	Dataset Used	Relevance	Limitation
[4]	Automatic detection of multiple eye diseases	CNN-DNN	Fundus	3000 images	ODIR	Classification module	Limited dataset size may affect generalization
[5]	Eye disease classification from fundus images	Pretrained CNN + Feature fusion (PCA)	Fundus	11,897 images	Multiple (e.g., OIH)	Feature-level fusion for DSS	Generalizability is unclear due to no external validation
[6]	Predicting eye diseases from OCT	Transfer learning	OCT	4000 images	Kaggle	Structural imaging input	Dataset imbalance may bias learning
[7]	Neurological disease diagnosis via eye movements	DL Framework	Eye movement (non-rectinal)	30 samples	Burnazyan Centre	Complementary diagnostic modality	Needs integration for broader applicability
[8]	Disease localization and segmentation	FRCNN + FKM	Fundus	1985 images	DiaretDB1, MESSIDOR, ORIGA	ROI detection for DSS	Not tested in real-time clinical workflow
[9]	Comparative study using clinical parameters	ML Models	Clinical	Not mentioned	Internal hospital dataset	Clinical data module	Dataset size undisclosed; reproducibility concern

Figure 1 shows limitation of MED detection. It has various problems, including the inability to evaluate robustness on a large dataset, difficulties with cross-modality image integration, and a lack of real-time datasets and multi-disease model validation. Because of these constraints, developing and evaluating many eye disease prediction models that can perform reliably and quickly in real-world settings is complex.

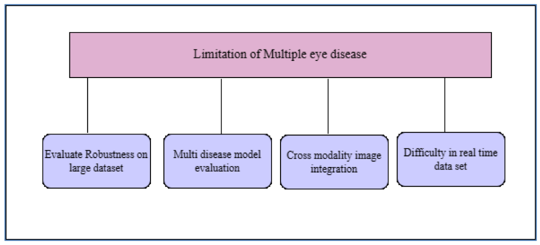

Figure 1. Exploring Limitations in MED Detection: A Diagrammatic Analysis

2.1 Comparative and Comprehensive Study

The Comparative Study in this review elucidates the symptoms and clinical features that are conventionally utilized to diagnose various ophthalmic conditions. Traditionally, clinicians have relied on the identification of symptoms such as microaneurysms, hemorrhages, optic nerve damage, and lens opacity to diagnose conditions including diabetic retinopathy, glaucoma, and cataracts. However, manual identification of these symptoms can be subjective and time-intensive. By leveraging advanced image processing techniques, computer vision, and deep learning architectures, these manual processes can be supplanted with artificial intelligence (AI) models that offer enhanced accuracy and efficiency in diagnosis. AI systems offer the automatic identification and quantification of these features from multiple imaging modalities, enhancing resolution and minimizing potential human errors in disease detection [Goel et al.,2021].

It is important to study is to automate a manual diagnostic processes to build effective AI framework. For example, diagnosing diabetic retinopathy—understanding how clinicians detect microaneurysms and hemorrhages can help guide the development of AI models that can automatically spot these characteristic findings in optical coherence tomography (OCT) or fundus images. Likewise, knowing which regions are examined in glaucoma to determine damage to the optic nerve allows AI models to concentrate on these areas in Heidelberg Retina Tomograph (HRT) scans. This knowledge ensures that AI models not only replicate but exceed human diagnostic capabilities by providing faster, more reliable, and highly accurate predictions for various eye diseases [Bourne et al.,2013].

Table 3. MED Clinical Data and Symptoms Comparison

Type	Clinical Diagnosis	Symptoms	Primary Affected Area	Vision Loss
Diabetic Retinopathy	●High blood sugar levels ●High blood pressure ●High cholesterol ●Smoking ●Long-term diabetes ●Obesity	●Eye floaters ●Blurriness ●Black spots in vision ●Loss of central vision ●Blindness	Retina	Gradual, peripheral
Glaucoma	●High blood sugar ●Elevated Intraocular Pressure (IOP) ●Optic nerve damage ●Visual acuity reduction ●Age-related risk	●Tunnel vision ●Blindness	Optic nerve	Peripheral (tunnel)
Cataract	●Diabetes duration ●Aging (senile) ●Genetics ●Smoking ●UV exposure ●Obesity	●Cloudy/blurred vision ●Glare/sensitivity to light ●Difficulty with night driving ●Yellowing of colors ●Frequent lens prescription changes	Eye lens	Central
Diabetic Macular Edema	●High blood sugar ●High cholesterol ●High blood pressure ●Kidney disease ●Smoking ●Genetics ●Caucasian ethnicity	●Distorted central vision ●Trouble reading or recognizing faces ●Washed-out colors ●Visual distortion ●Central vision loss or blind spot	Macula (retina)	Central and peripheral

Table 2. MED Image Modalities and Feature Comparison

Disease	Image Modalities	Ophthalmoscope Inference	Image Features	Level
Diabetic Retinopathy	OCT, HRT, Fundus images	Microaneurysm, haemorrhages, hard exudates, cotton wools, abnormal new vessels	• Normal retinal appearance • Microaneurysms • Hemorrhages • Venous beading • Neovascularization, fibrous tissue	0: No DR 1: Mild NPDR 2: Moderate NPDR 3: Severe NPDR 4: Proliferative DR
Glaucoma	OCT, HRT, Fundus images	Cup-to-disc ratio, neural retinal rim, parapapillary atrophy	• Slight visual field loss, slight cupping • Moderate visual field loss, moderate cupping • Severe visual field loss, large cupping	Mild Moderate Severe
Cataract	OCT, HRT, Fundus images	Mean intensity, uniformity, std. deviation, entropy	• Slight to dense lens opacities • Reduced lens transparency • Advanced cataract characteristics	Mild Cataract Severe Cataract
Diabetic Macular Edema	OCT, HRT	Retinal thickness measurement	• Cysts on OCT • Retinal thickening in macula • Fluid accumulation	Presence / Absence Macular thickness

The above table 2 presents various features that are used to identify each eye disease, along with its imaging technology, which is used to examine its features. The basic modalities that have been used are OCT (Optical Coherence Tomography), which is an eye imaging technique that uses light for in-depth retina scans. The topography of the optic nerve head can be mapped using the HRT (Heidelberg Retinal Tomograph), a tool for glaucoma diagnosis and monitoring. A fundus image, which captures the retinal image as well as the optic nerve and blood vessels, is a helpful instrument for assessing different eye conditions [Goel et al.,2021], [Bourne et al.,2013], [Safi et al.,2018], [Mishra et al., 2022].

The above table 3 presents additional information like clinical diagnosis and symptoms, which are used to identify various eye diseases. These data can be combined to raise the accuracy level of the automatic diagnosis of any eye diseases [Alyoubi et al., 2020], [MedicalNewsToday], [Healthline], [Li et al., 2019], [Harangi et al.,2019].

2.2 MED Diagnosis Framework

The stages of MED framework with methods are given in Figure 2. The workflow is designed to explain the techniques involved in each stage of handling image and clinical dataset [Phan et al., 2019], [AlGhamdi et al., 2019], [Asaoka et al., 2019].

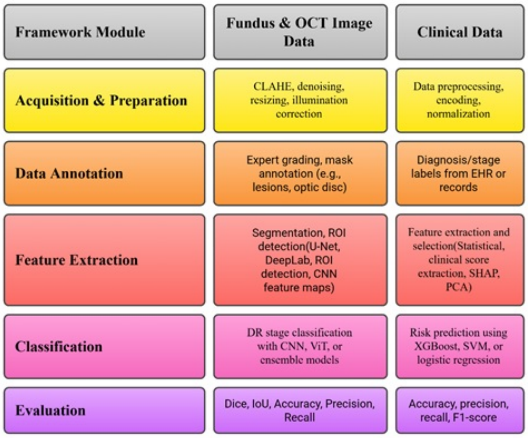

Figure 2. Unified MED Workflow

The workflow is divided into vertical modules, which are based on the specific type of dataset. Let us understand the workflow of unstructured datasets. It consists of image acquisition and preprocessing. The images are divided into different classes by identifying various ocular conditions such as normal, diabetic retinopathy, glaucoma and macular degeneration.The images are grouped according to the diseases to which they relate; therefore, the model is able to identify the distinguishing characteristics attached to each disease. In each stage of the module, many techniques are used for effective feature extraction and classification. Different preprocessing techniques, including contrast and noise adjustment, have been performed to clean the noise in the image dataset and to normalise the input for further downstream analysis. Depending on the model, the size of the images is normalised to obtain the same dimensions (if needed) and similar intensity values across various datasets. After normalisation, the images are sent to segmentation, which focuses on marking important anatomical structures such as the retina or optic disc. This step helps focus the algorithm on regions of clinical interest. After segmentation, Region of Interest (ROI) detection is carried out to identify specific characteristics, eg., lesions or other abnormalities related to the disease, for better analysis [Bajwa et al., 2019], [Lu et al.,2020], [Ramani et al., 2020].

Segmentation and ROI detection are performed as two completely distinct steps, as they serve different purposes. While segmentation is the general procedure of dividing the entire image into various regions to allow the algorithm to focus on corresponding anatomical parts, it splits the foreground structures like the retina from the background and detects most of the important structural elements of the eye. On the other hand, ROI detection looks deeper into specific areas within these segmented regions—for instance, lesions or microaneurysms within the retina. This detailed approach allows the system to highlight what might be the most significant image features related to certain eye diseases. By separating each stage, the system ensures that the image undergoes systematic processing, which facilitates increased diagnostic precision [Zhang et al., 2019], [Torre et al., 2020].

Another vertical workflow involves structured data, which includes details such as patient-specific clinical information—age, blood pressure, HbA1c level, and medical history. These data then undergo a systematic iterative process beginning with data acquisition from clinical records, followed by multiple steps of data cleaning and normalisation that ensure consistency and comparability across variables [Bourne et al., 2013b], [Congdon et al., 2004]. After preprocessing, the important clinical features for identifying each MED condition are extracted using feature selection algorithms. Classification algorithms such as XGBoost, Random Forest, etc., have been used in identifying the type of MED based on the selected feature in the previous step. The developed MED framework is evaluated using metrics such as accuracy, precision, recall, and F1 score. This organised data pipeline provides a stable platform for MED identification within a data-driven decision-making system [Li et al., 2021], [Rekhi et al., 2017] .

2.3 History of Segmentation Techniques in MED Prediction:

The segmentation techniques utilized in MED detection, is illustrated in Figure 3, It has been evolved from rudimentary methods such as thresholding, region growing, and edge detection in the 1990s to sophisticated deep learning hybrid models. During the 2000s, methodologies including K-means clustering, active contour models, graph cut, and watershed significantly enhanced anatomical localization of complex eye anatomy. Between 2015 and 2018, advancements in deep learning models such as Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), U-Net, and DeepLab facilitated pixel-wise accuracy for segmentation of retinal layers and features [Nazir et al., 2021], [Zago et al., 2020], [Kunwar et al., 2015].

Convolutional Networks (FCNs), U-Net, and DeepLab enabled pixel-level precision in segmenting retinal layers and features.CNNs are characterized by the equation

$$y = f(W * x + b)$$

Where W represents the weights, x is the input, and b is the bias. U-Net's efficacy is attributed to its encoder-decoder structure with skip connections. Its segmentation accuracy is commonly quantified using Dice Loss:

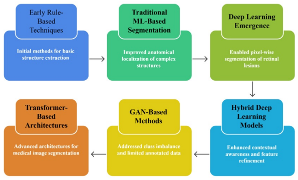

Figure 3. Evolution of Segmentation Techniques in MED

$$DiceLoss = 1 - \frac{2|A \cap B|}{|A|+|B|}$$

DeepLab, employing atrous convolutions, is defined by:

$$y|i| = \sum_K x[i + r \cdot K]w[k]$$

where r is the dilation rate, extending the receptive field for better segmentation. From 2019 to 2020, hybrid models like Mask R-CNN, Residual U-Net, and Attention U-Net further enhanced segmentation. Mask R-CNN loss includes:

$$L = L_{cls} + L_{box} + L_{mask}$$

while Residual U-Net improves feature extraction with residual connections:

$$y = f(x) + x$$

Attention U-Net applies attention mechanisms to refine focus on relevant image regions:

$$\alpha = \sigma(W_{att} \cdot (x_{enc} \oplus x_{dec}))$$

Since 2020, the availability of methods (eg., CycleGAN, Pix2Pix) for synthesizing retinal images has given developers flexibility to combine simple procedure and benefit (ie., limited dataset and dataset label imbalance). This resulted in a remarkable increase of the robustness and generalizability of segmentation models in rare or less frequent disease stages. In 2021 and beyond, transformer-based models like SegFormer capture long-range dependencies using the attention mechanism:

$$Attention(Q, K, V) = softmax(\frac{QK^t}{\sqrt{d_k}})$$

For achieving high segmentation accuracy, these models use a combination of cross entropy and Dice loss. Although loss functions such as Dice Loss and cross entropy are important, U Net and DeepLab are built on strong architectures, access to large amounts of high-quality annotated data, and powerful optimization technique. Focusing on this interplay gives a view of segmentation performance that is more complete. Such has made MED predicting machines more accurate and more rapid and thus more life-enhancing by diagnosing other diseases such as diabetic retinopathy etc.[Quigley et al., 2006], [Bourne et al., 2017], [AlBander et al., 2018], [Chen et al., 2015], [Mary et al., 2016], [Ayub et al., 2016].

2.4 MED Performance Evaluation

The deeper evaluation of these model results would lead to the acquisition of significant knowledge regarding model efficiency in identifying ocular diseases. Figure 4 represents five key metrics used in analyzing MED. This close examination of performance differences is helpful not only in selecting the most appropriate diagnostic model but also in evaluating its strengths and weaknesses. By assessing these metrics, researchers can identify areas where existing models perform well or poorly, encouraging targeted efforts to address weaknesses and develop more robust diagnostic systems for predicting MED. This iterative process of evaluation and improvement is crucial for advancing the field and ultimately improving patient care by providing more accurate and reliable diagnostic tools [Sarkar et al., 2017], [Nawaldgi et al., 2018], [Septiarini et al., 2018], [Zou et al., 2018], [Chudzik et al., 2018].

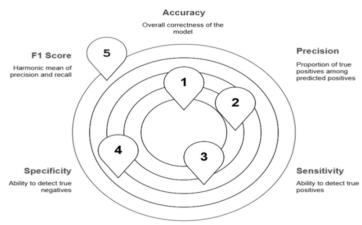

Figure 4. Performance Metrics used in MED

2.5 Data Privacy and Ethical Guidelines for AI in Ophthalmology

The following table 4 presents the Data Privacy and Ethical Guidelines by using WHO'S guideline for health that must be adhered to in order to ensure the safe and responsible development and implementation of AI models in ophthalmology. Compliance with these principles aids in safeguarding patient data, maintaining trust, and meeting regulatory standards while ensuring that AI tools support clinicians in enhancing patient care [Chen et al., 2020], [Faizal et al., 2023], [Liu et al., 2022], [Patankar et al., 2021], [Kuppusamy et al., 2022].

2.6 Real-World Testing and Performance Evaluation for AI in Ophthalmology

Real-world testing is crucial for AI and models to seamlessly integrate into high-impact workflows, managing diverse patient data and real-time demands. This testing evaluates the model's practicality, reliability, and scalability in routine healthcare operations. Figure 5 outlines critical aspects of real-world testing, such as clinical integration, system compatibility, and key performance indicators (eg., accuracy, efficiency, false positive/negative rates). It also assesses AI's impact on patient care, ensuring improvements in diagnosis and treatment outcomes. The system is then honed based on clinician feedback, with performance trends visually tracked.

Table 4. Key Data Privacy and Ethical Guidelines for AI in Ophthalmology

Category	WHO Guideline	Compliance	Key Practice
Privacy Laws	Upholding Personal Data Protection	Secure, anonymized patient data handling	Anonymization, encryption
Data Security	Ensuring Data Integrity and Confidentiality	Protect from breaches, unauthorized access	Encryption, access control
Ethical Use	Promoting Equity and Inclusiveness	Prevent discrimination, ensure trust	Diverse datasets, explainable AI
Consent	Protecting Human Autonomy	Ensure patient awareness, agreement	Clear communication, legal compliance
Regulations	Promoting Human Well-Being and Safety	Adhere to medical device regulations	Regulatory approval, safety checks
Human Oversight	Ensuring Transparency and Accountability	Support, not replace human judgment	Assist clinicians, retain accountability

The solution undergoes testing across different clinical scenarios to validate its generalizability [ambyal et al., 2020], [Almazroa et al., 2015], [Ramzan et al., 2019], [Phan et al., 2016], [Samagaio et al., 2018]. Several studies have shown successful real-world applications of AI especially in the field of ophthalmology. Li et al. based on 47,269 individuals in China with sensitivity and specificity of the AI model being very high [Li et al., 2021]. Gulshan et al. analyzed performance variability of several different systems that are approved in the US by the FDA [Gulshan et al., 2019]. Kanagasingam et al. found a 100% sensitivity using THEIA system at new zealand clinics [Kanagasingam et al., 2022], [Plotnikov et al., 2019]. Standardization of real-world evaluation is enabled by many benchmark datasets such as Messidor, REFUGE and DRIONS-DB.

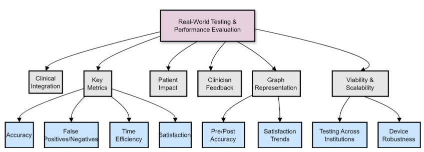

Figure 5. Real-World Testing and Performance Evaluation Framework

3 Overall Summary

This review focuses on identifying the gaps in developing an AI-based, data-driven framework that could diagnose diabetic ocular complications in terms of MED. It highlights the drawbacks of previous diagnosis systems which could only detect one kind of disease and helps in understanding the AI-based cutting-edge segmentation methods for anatomical analysis from fundus imaging and optical coherence tomography (OCT), such as U-Net, SegFormer, etc. A MED framework is presented in the review, including important steps and methods involved in each stage, such as preprocessing, segmentation, and classification. Therefore, AI offers promising solutions for predicting all stages of disease, starting from early detection till advanced stage. It also focuses on ensuring the reliability of models, addressing ethical considerations and safeguarding data privacy. Additionally, the review emphasizes the importance of improving diagnostic accuracy and achieving practical implementation of AI models in real-world ophthalmic practices. By emphasizing the crucial areas for advancement and further improvement, this study establishes the groundwork for future studies and advancements in AI-driven solutions in the field of ophthalmology.

4 Conclusion

This review provides a thorough analysis of the challenges and solutions involved in developing a MED framework. This also highlights the importance of clinical data using image datasets to improve the framework from early detection to other stages of diagnosis. It also goes beyond simply highlighting the gap in developing the MED framework by critically investigating the technical workflow in each stage of building the data-driven MED model. The review also examines the evolution of segmentation techniques, with a focus on modern approaches like GAN, U-Net and SegFormer, and evaluates the steps in constructing an efficient, adaptable AI-based MED framework. Considering the sensitivity of medical data and the possible consequences for decisions on patient care by AI, this emphasis on ethical considerations is highly relevant. Future work should endeavour to overcome these limitations with better integration of datasets, improved segmentation techniques, and ensuring ethical use, leading to more effective and robust AI healthcare solutions. This review helps in improving the accuracy and scalability of diagnosis and also helps in building a complete decision support system that can handle structural and unstructured data.

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