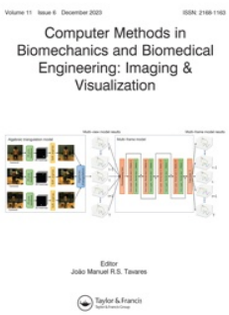

Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization

ISSN: 2168-1163 (Print) 2168-1171 (Online) Journal homepage: www.tandfonline.com/journals/tciv20

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To cite this article: Shraddha S. Shinde & Swati A. Bhavsar (2026) Comprehensive study of ophthalmic diseases: insights, challenges and innovations, Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 14:1, 2380091, DOI: 10.1080/21681163.2024.2380091

To link to this article: https://doi.org/10.1080/21681163.2024.2380091

Published online: 15 Feb 2026.

COMPUTER METHODS IN BIOMECHANICS AND BIOMEDICAL ENGINEERING: IMAGING & VISUALIZATION
2026, VOL. 14, NO. 1, 2380091
https://doi.org/10.1080/21681163.2024.2380091

Comprehensive study of ophthalmic diseases: insights, challenges and innovations

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ABSTRACT

Ophthalmic diseases establish a vital global health concern, affecting millions of persons worldwide and affect vision loss which increases impact on the quality of life and economic burden. Classifying diseases is a crucial aspect of the ophthalmology, as it helps in diagnosis, treatment and research. It encompasses a wide range of conditions affecting the eyes and its surrounding. The classification can be based on anatomy, clinical presentation, age-related factors, systemic associations and traumatic causes. Ophthalmologists use these classifications to provide targeted treatments and interventions. In this review paper, we converse the impact of diseases on individuals and society, and image modalities used to classify and detect disease with severity. Additionally, this study explores risk factors along with the need for dedicated research, intervention strategies, diagnosis challenges and proposed system. By understanding the various circumstances, this study helps to diagnose the eye disease with its severity. This study reveals that 28% of researchers used the Messidor dataset with 24% applied CNN techniques, along with 57% diseases focusing on diabetic retinopathy. Despite existing methods, there is scope for improvement in detecting multiple ophthalmic diseases, which the proposed system aims to address by enhancing detection and classification with severity within a single framework.

ARTICLE HISTORY
Received 6 November 2023
Accepted 10 July 2024

KEYWORDS
Ophthalmic diseases; OCT; fundus photographs

1. Introduction

The era of ophthalmology is dedicated to the study and management of diseases and disorders related to the eye and the visual system. Ophthalmic diseases encompass a wide range of conditions, from common and easily treatable issues like refractive errors to severe and potentially blinding diseases such as glaucoma, age-related macular degeneration (AMD), diabetic retinopathy and cataract. These conditions can affect individuals of all ages and backgrounds, making them a significant global health concern.

The eye is a remarkably complex and delicate organ responsible for our sense of vision. Ophthalmic diseases can impact several eye portions, including lens, cornea, optic nerve, retina and the surrounding structures like the eyelids and tear ducts. These diseases can be visible with a diverse array of symptoms, from blurred vision and eye discomfort to pain, redness, and, in severe cases, vision loss.

Understanding ophthalmic diseases is crucial because vision is a fundamental aspect of human well-being and quality of life. Impaired vision can hinder daily activities, limit independence and reduce overall life satisfaction. Furthermore, untreated ophthalmic diseases can progress to irremediable vision loss, making early detection and intervention critically important.

The causes of ophthalmic diseases vary widely and can include genetic factors, infections, autoimmune processes, age-related changes and environmental influences. Risk factors such as smoking, poor nutrition and exposure to UV radiation can also contribute to the development and progression of these conditions.

Ophthalmologists, eye care specialists trained to diagnose and treat ophthalmic diseases, play a pivotal role in addressing these conditions. They utilise a range of diagnostic tools, including visual acuity tests, ophthalmoscopy, imaging techniques like optical coherence tomography (OCT) and various specialised tests to evaluate the health of the eye and identify specific diseases.

Treatment options for ophthalmic diseases are equally diverse and may include prescription eyeglasses or contact lenses, medications (e.g. eye drops), surgical procedures (e.g. cataract surgery or laser therapy), and, in some cases, innovative approaches like gene therapy and regenerative medicine.

In this era of advancing medical technology, ongoing research and innovation in ophthalmology are expanding our understanding of these diseases and leading to more effective treatments. Additionally, public health initiatives aim to encourage eye health, nurture awareness about the significance of regular eye exams and improve access to eye care services, especially in underserved communities.

In brief, ophthalmic diseases represent a multifaceted and significant aspect of healthcare. This introduction provides a glimpse into the complex world of eye-related conditions, emphasising their impact on individuals' lives and the critical role of healthcare providers and researchers in their diagnosis, treatment and prevention. As our knowledge and technology continue to advance, we strive to enhance our ability to preserve and restore vision, thereby improving the quality of life for millions of individuals across the world.

This review aims to be responsible for a holistic understanding of ophthalmic diseases, considering their prevalence, risk

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factors, diagnostic challenges and recent advancements with their limitations also summarise the ophthalmic diseases, emphasising their global prevalence and distribution among different populations. This study provides a brief introduction to the proposed system and outlines its future directions. It explores the impact of demographic factors, including age, gender and geographic location, on the incidence of these diseases. Section II explains the importance and impact of ophthalmic diseases, section III classifies the various ophthalmic diseases and their symptoms and section IV discusses the causes and risk factors of diseases. Section V states diagnostic challenges for ophthalmic diseases detection. Section VI elaborates techniques and image types used by the researchers. Section VII briefs the proposed system. Finally, this paper concludes with discussion and conclusion.

2. Importance and impact of ophthalmic diseases

In this section, the importance and impact of ophthalmic diseases on individuals and society is explained. These diseases affect people of all ages and backgrounds. These diseases not only impact an individual's quality of life but also have broader societal and economic implications. Investing in preventive measures, early intervention and ongoing research into ophthalmic diseases is essential to reduce their impact and improve the lives of those affected by these conditions. Here is a detailed explanation of their impact:

2.1. Individual impact

- Vision Loss and Impairment: Ophthalmic diseases can direct to vision loss completely or partially, which considerably affects an individual's capability to perform daily activities independently. Loss of vision can lead to a decreased quality of life, reduced mobility and increased dependence on others.
- Physical and Mental Health: Visual impairment can result in physical injuries due to falls and accidents. Moreover, it can prime to mental and emotional health issues viz. anxiety and depression and results in the loss of freedom and social isolation.
- Educational and Occupational Limitations: Children with untreated eye conditions may experience difficulties in learning and academic achievement. Similarly, adults may face challenges in maintaining employment or pursuing their careers when vision is compromised.
- Impact on Relationships: Vision loss can strain personal relationships, as individuals may become reliant on family members for assistance with daily tasks. This can affect the emotional well-being of both the affected individual and their caregivers.

2.2. Societal impact

- Economic Burden: Ophthalmic diseases impose a generous financial burden on society. This includes costs associated with healthcare, diagnosis, treatment and rehabilitation, as well as indirect costs related to productivity losses due to vision impairment or blindness.
- Increased Healthcare Utilisation: Ophthalmic diseases often require frequent medical visits, surgical interventions and long-term management, contributing to the demand for healthcare services. This can strain healthcare systems and resources.
- Educational and Employment Impact: Vision-related difficulties can lead to lower educational attainment and reduced employment opportunities. This can result in a less skilled workforce and decreased economic productivity at both individual and societal levels.
- Social Welfare Programmes: Vision-impaired individuals may require social welfare and disability support, further impacting government budgets and resources.
- Public Health Concern: Ophthalmic diseases are a significant public health concern. They may be indicative of broader health issues, such as diabetes or hypertension, and can lead to complications that affect overall well-being.

2.3. Prevention and intervention

- Early Stage Detection and Treatment: The impact of ophthalmic diseases can be mitigated through early stage detection and proper treatment. Regular eye exams can help identify conditions at their earliest stages when interventions are most effective.
- Vision Rehabilitation: Rehabilitation services, including vision aids, adaptive technology and training programmes, can help individuals with visual impairment regain independence and improve their quality of life.
- Public Awareness and Education: Promoting civic awareness of healthy eyes and the importance of regular eye check-up can contribute to the early detection and prevention of ophthalmic diseases.

3. Classification of ophthalmic diseases

There are numerous categories of ophthalmic diseases, each with its own unique characteristics and manifestations. Ophthalmic diseases can be categorised based on anatomy, aetiology, clinical presentation, age-related factors, systemic associations and traumatic causes. In Figure 1, classification with their subcategory is mentioned. Symptoms of each category with its detection methodologies are mentioned in Table 1.

- Refractive Errors:
  - o Myopia: Difficulty to see clearly distant objects.
  - o Hyperopia: Difficulty to see visibly nearer objects.
  - o Astigmatism: Blurred vision or distorted vision due to irregular shape of cornea or lens.
  - o Presbyopia: Age-related difficulty in focusing on close objects.

- Cataracts:
  - o Age-related cataracts: Clouding of the eye's natural lens due to ageing.

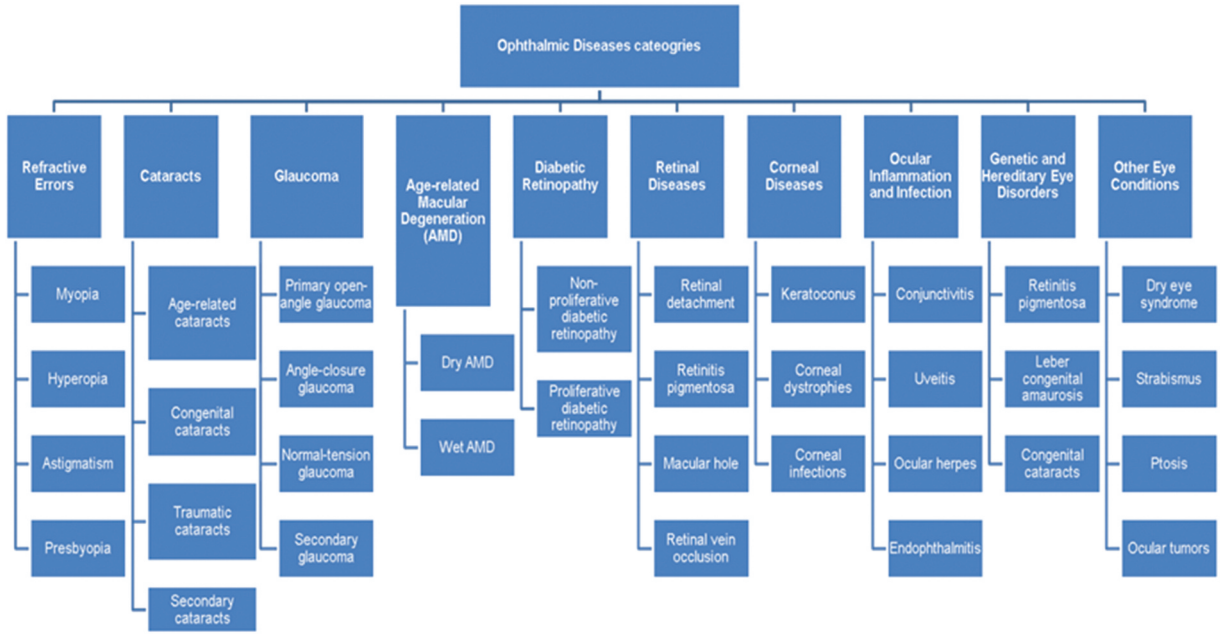

Figure 1. Classification ophthalmic diseases.

o Congenital cataracts: Present at birth or develop during infancy.
o Traumatic cataracts: Result from eye injuries or trauma.
o Secondary cataracts: Develop as a result of other eye conditions or systemic diseases.

- Glaucoma:
  - o Primary open-angle glaucoma: Gradual damage to the optic nerve with increased intraocular pressure.
  - o Angle-closure glaucoma: Sudden increase in intraocular pressure due to a narrow drainage angle.
  - o Normal-tension glaucoma: Optic nerve damage despite normal intraocular pressure.
  - o Secondary glaucoma: Caused by other eye conditions, trauma or systemic diseases.
- Age-Related Macular Degeneration (AMD):
  - o Dry AMD: involves the gradual breakdown of the macula.
  - o Wet AMD: Due to abnormal growth of blood vessel under the macula causes scarring and fluid leakage.
- Diabetic Retinopathy:
  - o Non-proliferative: Weakening of retinal blood vessel and potential fluid leakage.
  - o Proliferative: new blood vessels grow on retinal abnormally.
- Retinal Diseases:
  - o Retinal detachment: Retina is separated from its underlying tissue.o Retinitis pigmentosa: Vision loss occurs due to retinal progressive degeneration.
  - o Macular hole: A small break or defect in the macula.
- Corneal Diseases:
  - o Keratoconus: Progressive thinning and bulging of the cornea.
  - o Corneal dystrophies: Genetic disorders affecting the cornea's structure and clarity.o Corneal infections (e.g. bacterial, viral, fungal).
- Ocular Inflammation and Infection:
  - o Endophthalmitis: Severe infection within the eye.
  - o gConjunctivitis (pink eye): Inflammation of the conjunctiva.
  - o Uveitis: uvea and eye's middle layer's inflammationo
  - o Ocular herpes: Viral infection affecting the eye.
- Genetic and Hereditary Eye Disorders:
  - o Retinitis pigmentosa: Inherited disorder causing progressive vision loss.
  - o Leber congenital amaurosis: Genetic disorder leading to severe visual impairment from birth.
  - o Congenital cataracts: Present at birth due to genetic factors.
- Other Eye Conditions:
  - o Dry eye syndrome
  - o Strabismus (misalignment of the eyes)
  - o Ptosis (drooping eyelids)
  - o Ocular tumours (e.g. retinoblastoma)

4. Causes and risk factors

Understanding the risk factors associated with ophthalmic diseases is crucial for prevention and early intervention. This section discusses genetic predisposition, lifestyle factors, systemic diseases and environmental influences that contribute to the development of various ocular conditions.

The causes and risk factors mentioned here are not exhaustive, and individual cases may have unique factors contributing to the development of ophthalmic diseases. It is always recommended to consult with an ophthalmologist or eye care professional for

Table 1. Symptom of ophthalmic diseases.

Classification	Sub Category	Symptoms	Detecting Methods
Refractive Errors	Myopia	Nearsightedness (−ve number specs): Blurry vision when look at long distance objects.	Visual Acuity Test, Retinoscopy, Refraction Test:
	Hyperopia	Farsightedness (+ve number specs): blurry vision when look at nearer object.	
	Astigmatism	Distorted or blurry vision at any distance.	
Cataracts	Age-related, Congenital, Traumatic and Secondary cataracts	Cloudy or blurry vision. Sensitivity to glare, especially at night. Difficulty seeing in dim light. Fading or yellowing of colours.	Visual Acuity Test, Slit-Lamp Examination, Retinal Examination
Glaucoma	Angle-closure, Primary open angle, Normal-tension and Secondary glaucoma	Increased intraocular pressure. Tunnel vision or peripheral vision loss gradually Blurred vision. Halos around light (Diffraction) Rigorous eye pain (in acute angle-closure glaucoma).	Tonometry, Ophthalmoscopy, Perimetry, OCT
Age-Related Macular Degeneration(AMD)	Dry AMD, Wet AMD	Central vision loss or distortion Blurred or wavy central vision Difficulty recognising faces or reading	Amsler Grid Test, Fundus Photography, Fluorescein Angiography, OCT
Diabetic Retinopathy	Non-proliferative and Proliferative diabetic retinopathy	fluctuating or blurred vision Empty or dark areas in the vision field. (scotomas) Floaters Difficulty seeing at night	Dilated Eye Examination, Fluorescein Angiography, OCT
Retinal Diseases	Macular hole, Retinal detachment, Retinal vein occlusion and Retinitis pigmentosa	Sudden onset of flashes of light (photopsia) Floaters. Shadow or curtain over part of the visual field Rapid decrease in vision.	Fundus Photography, OCT, Ultrasound
Corneal Diseases	Keratoconus, Corneal dystrophies, Corneal infections	Sensitivity Eye pain Blurry vision Red or bloodshot eyes Pus or discharge	Corneal Topography, Slit-Lamp Examination, Pachymetry
Ocular Inflammation and Infection	Conjunctivitis (Pink Eye)	Redness and irritation of the conjunctiva. Watery or pus-like discharge. Itchy or gritty sensation. Swollen eyelids	Slit-Lamp Examination, Ophthalmoscopy, Fundus Fluorescein Angiography
	Uveitis	Eye pain Redness Blurred vision Photophobia Floaters	
Other Eye Conditions	Strabismus (Crossed Eyes)	Misalignment of the eyes. Double vision. Decreased depth perception.	comprehensive eye examination, cover testing, slit lamp examination
	Dry Eye Syndrome	Gritty or sandy feeling in the eyes. Redness. Excessive tearing (paradoxical dryness). Blurred vision	

a comprehensive evaluation and personalised risk assessment. The detailed explanation of common causes and risk factors associated with ophthalmic diseases is mentioned below.

4.1. Refractive errors

- Causes: Refractive errors arise when the eye shape prevents light from directing on the retina. Common causes include variations in the length of the eyeball, the corneal curvature or the lens' shape.
- Risk Factors: Risk factors for refractive errors include genetic predisposition, hereditary of refractive errors, medical circumstances viz. diabetes, environmental factors (such as excessive near work or prolonged screen time) and age-related changes in the lens.

4.2. Cataracts

- Causes: Cataracts result from the gradual breakdown and clouding of the natural lens inside the eyes. The main cause is age-related degeneration, where proteins in the lens become less transparent and clump together. Other causes include genetic factors, eye trauma, exposure to ultraviolet radiation, certain medications (such as corticosteroids) and systemic conditions like diabetes.
- Risk Factors: Advancing age is the most significant risk factor for cataracts. Other risk factors include a family history of cataracts, smoking, excessive sunlight exposure, obesity, prolonged use of corticosteroids, certain medical conditions (e.g. diabetes, hypertension) and previous eye surgeries or injuries.

4.3. Glaucoma

- Causes: The primary reason of glaucoma is by increasing the intraocular pressure, which results into the damages of the optic nerve. The exact causes change from the type to type of glaucoma. In the primary Open-Angle glaucoma disease, the drainage system of the eye becomes less efficient over time, leading to increased pressure. The iris blocks the drainage angle due to which angle-closure glaucoma occurs and results in a sudden rise in eye pressure.
- Risk Factors: It includes age factor, hereditary or family history, certain ethnic backgrounds (e.g. African, Asian), elevated intraocular pressure, thin corneas, previous eye injuries or surgeries, some medical circumstances viz. diabetes, high-level blood pressure and long-term use of corticosteroids.

4.4. Retinal diseases

- Causes: Retinal diseases can have various causes, depending on the specific condition. Some are genetic in nature, resulting from inherited mutations in genes responsible for maintaining retinal health. Age-related changes, such as macular degeneration, are attributed to cumulative damage to the retina over time. Vascular diseases affecting the retinal blood vessels can restrict blood flow, leading to retinal ischaemia. Other causes include eye trauma or injury, autoimmune disorders and certain infections.
- Risk Factors: These retinal diseases involve a family history (hereditary), advancing age, certain genetic disorders (e.g. retinitis pigmentosa), systemic diseases (e.g. diabetes, hypertension), smoking, excessive alcohol consumption, prolonged exposure to sunlight and certain medications (such as hydroxychloroquine).

The anatomy of the human eye with highlighted retinal structure is shown in Figure 2 (Thomas 2004). It contains major parts as cornea, iris, pupil, lens, macula, retina, optic nerve, etc. The brief function of these parts is mentioned below.

- **Cornea**: Focuses light onto the retina.
- **Iris**: Regulates pupil size and light entry.
- **Pupil**: Lets light into the eye.
- **Lens**: Focuses light on the retina.
- **Retina**: Converts light to electrical signals.
- **Optic Nerve**: Transmits visual information to the brain.
- **Ciliary Body**: Adjusts vision focus.
- **Macula**: Provides sharp, detailed vision.

The fundus image for normal and different ophthalmic diseases observed such as cataract and diseases which affect the retina viz. glaucoma, diabetic retinopathy-DR, AMD, macular degeneration, retinoblastoma, high myopia and RVO are shown in the following Figures 2(a–i).

5. Diagnostic challenges for ophthalmic diseases detection

Detecting ophthalmic diseases can be challenging due to various factors, including the complexity of the eye's anatomy and the subtlety of some disease manifestations. Here are some common diagnostic challenges in ophthalmic diseases detection:

- Asymptomatic Early Stages: Many ophthalmic diseases, such as glaucoma and diabetic retinopathy, can develop silently in their early stages, without causing noticeable symptoms. This can delay diagnosis until the disease has progressed significantly.
- Variability in Symptoms: Some eye conditions, like dry eye syndrome or uveitis, can present with a wide range of symptoms that overlap with other common eye problems. This can lead to misdiagnosis or delayed diagnosis.
- Intermittent Symptoms: Patients with intermittent eye conditions, such as ocular migraines or episodic diplopia, may not exhibit symptoms during a clinic visit, making diagnosis challenge.
- Subtle or Non-specific Signs: Certain eye diseases may exhibit subtle or non-specific signs that are easily missed during routine examinations. For example, early retinal changes in some hereditary retinal diseases may not be apparent without specialised testing.
- Patient Compliance: Patients may not always adhere to recommended eye examinations or follow-up appointments, especially if they perceive their eye problems as minor or if they lack access to healthcare.
- Age-Related Changes: Some age-related changes in vision, like presbyopia (difficulty focusing on near

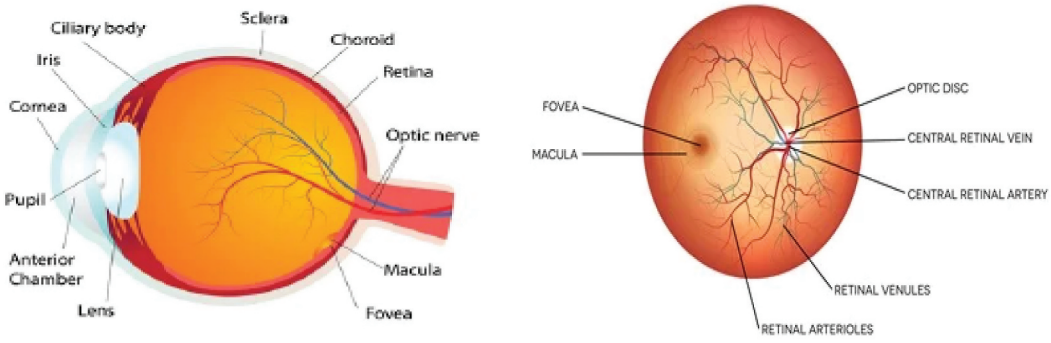

Figure 2a. Anatomy of human eye and features of retina (Thomas 2004).

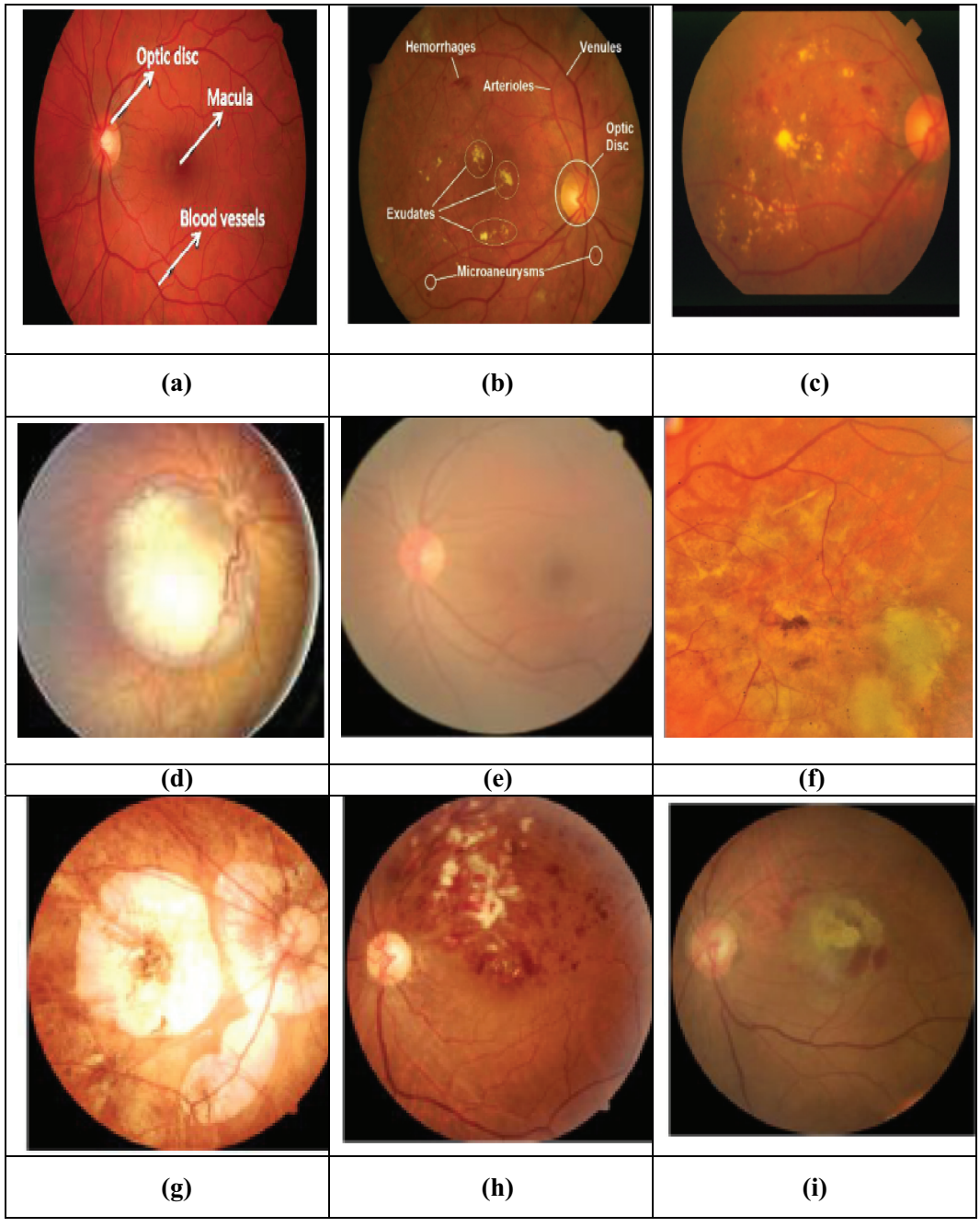

Figure 2b. a: Normal colour fundus image (Poonguzhali et al. 2018) (Elangovan and Kumar Nath 2019). b: symptoms of DR, Glaucoma (Poonguzhali et al. 2018). c: diabetic retinopathy. d: retinoblastoma. e: cataract. f: AMD. g: high myopia (Zhu et al. 2022). h: RVO (Zhu et al. 2022). i: macular degeneration (Zhu et al. 2022).

objects with age), can mimic the symptoms of more serious eye conditions, potentially leading to misdiagnosis.

- Limited Access to Specialised Care: In many regions, access to ophthalmic specialists and advanced diagnostic equipment is limited, making it challenging to diagnose and manage complex eye diseases.
- Coexistence of Multiple Conditions: Patients may have multiple eye conditions simultaneously, making it difficult to identify the primary cause of their symptoms.
- Patient Communication: Effective communication with patients, especially those with language barriers or cognitive impairments, can be challenging, which may hinder the collection of accurate medical histories and symptom descriptions.
- Variable Disease Progression: Some eye diseases progress at different rates in different individuals, making it challenging to predict when treatment or intervention is necessary.
- Rare and Unusual Conditions: Ophthalmology encompasses a wide range of rare and unusual conditions, and healthcare providers may not encounter these conditions frequently, leading to potential diagnostic challenges.

- Age-Related Eye Changes: Differentiating between age-related eye changes and pathological conditions can be tricky, particularly in older individuals.
- Diagnostic Equipment and Imaging Variability: The quality and availability of diagnostic equipment such as OCT or imaging devices can vary, affecting the accuracy of diagnosis in different settings.

To overcome these challenges, healthcare providers must stay updated on the latest diagnostic techniques, encourage regular eye examinations and consider referral to specialised eye care professionals when necessary. Additionally, advances in telemedicine and artificial intelligence may help improve the early detection of ophthalmic diseases, even in underserved or remote areas.

6. Techniques and image types

Detecting diabetic retinopathy (DR), AMD, Glaucoma, Cataract and Retinoblastoma have evolved significantly from 2008 to 2023, with advancements in technology and diagnostic methods. Here are some methods used for DR detection during this period:

- **Fundus Photography**: Fundus photography has been a cornerstone of DR and AMD detection. High-resolution images of the retina, macula and surrounding retina are captured using specialised cameras. Over the years, the quality and resolution of these images have improved, enabling better visualisation of microaneurysms, haemorrhages, and other DR-related changes as well as of drusen, pigment changes and macular atrophy (Salz and Witkin 2015).
- **Optical Coherence Tomography (OCT)**: OCT technology has become an increasingly vital and standard tool for both AMD and DR diagnosis. It provides cross-sectional images of retinal layers, allowing for the detection of the macular oedema, changes in retinal thickness and the assessment of retinal microstructure. SD-OCT (SD-Spectral domains) and SS-OCT (SS-swept source) have improved image resolution and speed (Saeed and Oleszczuk 2016).
- **Fluorescein and Indocyanine Green Angiography**: Though not as common as some other methods, fluorescein angiography has still been used during this period. It includes injecting a contrast dye into a patient's bloodstream and collecting captured images as the dye flows through the retinal blood vessels. This method helps in identifying vascular abnormalities (blood vessel growth and leakage) and classify AMD subtypes, such as neovascular (wet) AMD (Gajree et al. 2016).
- **Slit-Lamp Examination**: Ophthalmologists use a slit lamp to examine the eye's anterior segment, including the lens. Cataracts can be observed directly during this examination.
- Automated Image Analysis: Advances in artificial intelligence, deep learning and machine learning have led to automated fundus or other image analysis systems. These systems can detect and grade DR features like microaneurysms, haemorrhages, and exudates from fundus images. They have significantly improved the efficiency of DR screening programmes. Various image modalities used to detect and analyse the ophthalmic diseases shown in Figure 3.
- **Recent Advancement:** Performing a thorough survey in the field of ophthalmic diseases would involve an extensive review of scientific publications, research articles, review papers and medical experimental studies related to various ophthalmic conditions. Here, we provide a brief overview of some key topics and recent advancements in ophthalmic disease research.
  - o Diabetic Retinopathy (DR): DR is a significant cause of visual damage and loss of sight in individuals with diabetes. Recent research has focused on early detection and novel treatment strategies. Studies have explored the use of artificial intelligence (AI), deep learning (DL) and machine learning (ML) algorithms

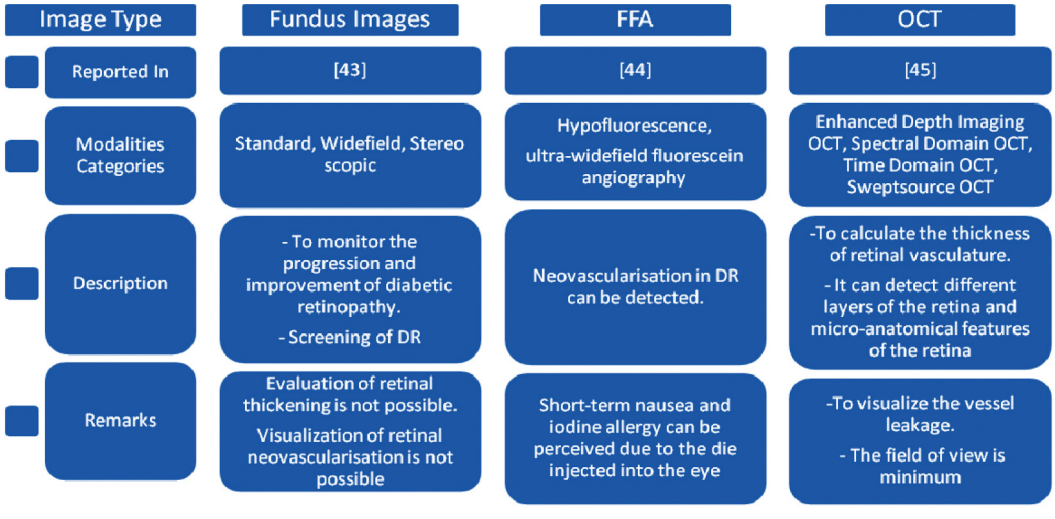

Figure 3. Images used in diagnosing ophthalmic disease (Dimple Nagpal et al. 2022).

for automated screening and grading of DR.

- Age-related Macular Degeneration (AMD): This is a foremost cause of partial or complete vision loss in adults. Research in this area has focused on understanding the pathogenesis of AMD, developing effective diagnostic techniques and identifying novel treatment modalities. Anti-VEGF therapy has changed the neovascular age-related macular degeneration (AMD) management, while emerging therapies like gene therapy and stem cell-based approaches are being investigated for their potential in treating both dry and wet AMD.
- Glaucoma: It is characterised by optic nerve impairment and progressive visual field loss. Recent research has focused on improving early detection and monitoring techniques. Advancements in imaging technologies, such as OCT and adaptive optics, have enabled more precise evaluation of the optic nerve and retinal structures. In addition, studies are investigating novel surgical techniques, minimally invasive therapies and neuroprotective agents to preserve optic nerve function and prevent further vision loss.
- Cataracts: Cataract surgical treatment is one of the most common procedures worldwide. Research in this area has focused on improving surgical techniques, optimising intraocular lens design and enhancing refractive outcomes. The development of advanced technology intraocular lenses (multifocal, extended depth of focus) aims to reduce dependence on glasses after surgery. Additionally, research is exploring pharmacological approaches to delay or prevent cataract formation.
- Dry Eye Disease: It is a multifactorial disorder characterised by insufficient tear production or poor tear quality. Recent studies have investigated the underlying mechanisms, including inflammation, neurosensory abnormalities and tear film instability. New treatments targeting specific pathways, such as anti-inflammatory agents, tear stimulation therapies and novel lubricants, offer potential for better management of dry eye disease.
- Retinal Detachment: Retinal detachment requires prompt diagnosis and surgical intervention to prevent permanent vision loss. Research efforts have focused on refining surgical techniques, including the use of small-gauge vitrectomy systems and advanced intraoperative imaging. Furthermore, studies are investigating adjunctive therapies such as pharmacological agents, retinal regeneration approaches and retinal prosthetics for enhancing visual outcomes after retinal detachment repair.
- It's important to note that the field of ophthalmic diseases is vast, and ongoing research continues to advance our understanding and treatment options for various conditions. Conducting a comprehensive literature survey would involve searching academic databases, consulting relevant journals and reviewing recent conference proceedings to gather an all-inclusive overview of the most recent research and advancements in the field.

The numerous researchers work from 2008 to 2023 on various ophthalmic diseases to detect and provide grading viz. no disease, mild, moderate, severe. Table 2 discusses disease-wise methods and dataset used by several researchers. Standard publically available datasets are considered by the various researchers for testing. Table 3 shows the analysis of datasets referred by the various researchers.

Recently, researchers widely used the machine and deep learning techniques to address the solution to detect and classify the ophthalmic diseases. Here, the techniques used by the various researchers are stated in the timeline charts. The timeline chart for Age-related Macular Degeneration (AMD), Diabetic Retinopathy (DR) and Glaucoma and Retinoblastoma are mentioned in Figures 4, 5 and 6 respectively. Table 4 comprises overview of innovative methods for detection of DR, AMD, Glaucoma and Cataract with its concluding remark and scope of improvement. The most of techniques used by the researchers do not provide single automated system for multiple ophthalmic diseases for severity grading and classification at early stage.

Table 5 involves analysis of performance metrics used by the various researchers in different diseases such as DR, AMD, Glaucoma and Retinal diseases with its concluding remark and scope of improvement. The most of researchers measured the performance of their innovative methods with respective to sensitivity, specificity and accuracy in various diseases.

7. Proposed system

This research proposes a novel system for the detection of multiple ophthalmic diseases and classifies its severity grades from fundus images at early stage so that the patients can recover fast and will protect their eyes from blindness and vision loss.

Our contribution for the proposed system is mentioned below.

- Preprocessing: Remove the noise (Gharaibeh et al. 2023) and enhance the image using CLAHE
- Apply the segmentation techniques (Thresholding and edge-based segmentation) to locate the features or ROI.
- Extract and select the features from fundus images
- Create the labelled dataset from the extracted feature
- Use selected features as input and apply Hybrid deep learning method to classify multiple ophthalmic diseases and its severity grade.
- Test and validate the proposed system with Standard Datasets which are publically available.

The Figure 7 shows the proposed system architecture. Here, we have brief the proposed system but our next study will focus on methods and algorithms used in proposed system in detail.

8. Discussion

This study discusses the various aspects related to diseases, datasets and techniques used by various researchers. As per Table 2, it has been observed that 57% researchers considered the diabetic retinopathy, 20% AMD, 5% cataract, 16% glaucoma and 2% retinoblastoma and retinal diseases for their studies and research.

Similarly, the researchers used various publicly available and private dataset to test and validate the system to detect ophthalmic diseases and grade them accordingly. As per Table 3, this

Table 2. Disease-wise methods and dataset used by several researchers (Dimple Nagpal et al. 2022).

Reported in	Researchers	Year	Algorithm/Methodology used	Dataset used	Brief of Images from Dataset
Diabetic Retinopathy					
Abràmoff et al. (2008, 2013)	Abramoff et. al	2008, 2013	Retrospective analysis done using non-mydriatic images, Iowa Detection programme	MESSIDOR, AREDS	Year 2008:7689 quality images) 640×640 pixel size, Year 2013:1748 images
Mohammad Alipour et al. (2012)	Hajeb Mohammad Alipour et. al	2012	CLAHE(Contrast limited adaptive histogram equalisation), Canny edge detector, SVM	Local dataset	FFA-70 images Fundus images-70 (576×720 pixels)
Esmaeili et al. (2014)	Esmaeili et. al	2014	Curvelet Transformation, Equalisation algorithm	Private Data	89 images
Imani et al. (2015)	Elaheh Imani et. al	2015	Morphological Component Analysis	MESSIDOR	1200 images (1440×960, 2240 × 1488or 2304 × 1536 pixel)
Solanki et al. (2015)	Solanki K. et. al	2015	EyeArt	MESSIDOR-2	850908 fundus images from 101,710
Dhara et al. (2015)	Dhara et. al	2015	Morphological features, CLAHE, SVM	MESSIDOR	1200 images
Rahim et al. (2016)	Rahim et. al	2016	FED, Decision tree (DCT), KNN	Eye Clinic Dataset, Melaka Hospital, Malaysia	600 images (3872×2592 pixels)
Gulshan et al. (2016)	Gulshan et. al.	2016	group of 10 Inception-Networks	EyePACS-1 & MESSIDOR-2	88702 images (35126 + 53576 training + testing)
Seoud et al. (2016)	Seoud et. al	2016	Candidate Extraction	Erlangen Roch, Diaretdb1, Messidor, CARA1006, & CARA143	Erlangen:45 Roch:100, Diaretdb1:89, Messidor:1200, CARA1006:1006, CARA143:143 images
Pratt et al. (2016)	Patt et. al	2016	Data Augmentation, CNN	Kaggle Dataset	80000 images
Gargeya and Leng (2017)	Gargeya et. al	2017	AI	Messidor, E-optha Private	75125 images
Lam et al. (2018)	Carson Lam et al	2017	CNN, GoogLeNet, Alexnet	Kaggle Dataset, Messidor-1	1200 images
Sil Kar and Maity (2017)	Kar and Maity et al	2018	OBP Filter Curvelet Based Edge,	Drive Stare DIARETDB1 Messidor	Drive Stare-400 images, DIARETDB1–189 images, Messidor-1200 images
Muhammad Saiful Islam and Abdullah (2018)	S. M. S.Islam et. al	2018	data augmentation, L2 regularization	Kaggle diabetic retinopathy dataset	88702 images
Leeza and Farooq (2019)	Leeza et. al	2019	x Bag of features, K Means	Kaggle National Data Science Bowl	390 from 35,126 images
Li et al. (2018)	Z. Li et. al	2018	Deep CNN, SVM	Dataset from Kaggle Contests	48116 fundus photographs
Shanthi and Sabeenian (2019)	Shanthi et. al	2019	CNN	Messidor	1200 images
Qummar et al. (2019)	Sehrish Qummar et. Al	2019	CNN, Iv3, Xception, D-121, D-169, Resnet50	Kaggle	88702 images
Long Zeng et al. (2019)	X. L. Zeng et. al	2019	Inception V-3	Kaggle DR competition	28104 images
Dorizzi et al. (2020)	B. Dorizzi et. al	2019	CNN, Probability map	DiaretDB1 and Messidor	DiaretDB1–189 images, Messidor-1200 images
Gao et al. (2019)	Z. Gao et. al	2019	Inception V-3	Lab Dataset	4476 images
Wang et al. (2019)	Wang et. al	2019	Logistic Regression	Lab Dataset	1589 images
Sakshi Gunde and Gupta (2020)	S. Gunde et. al	2020	Circular Hough transform, OTSU Algorithm,	DIARETDB0	120 images
Zhang et al. (2022)	Xiao Zhang et.al	2021	Hybrid CNN (EyeNet model and DenseNet model)	Kaggle Public Dataset	88702 images
Abdel Maksoud et al. (2022)	Eman AbdelMaksoud et. al	2022	Hybrid CNN (EyeNet model and DenseNet model)-CAD	EyePACS, APTOS, Messidor, IDRiD	APTOS 2019 dataset -18,590 colour fundus images, MESSIDOR dataset-1200 images, IDRiD dataset-516 images (256×256 pixels) EyePACS:9963 images
Suman et al. (2023)	Supriya Suman et. Al	2023	Learning based Random Forest classifier	Messidor, APTOS	APTOS :18590 images, MESSIDOR dataset-1200
Ting et al. (2017)	Ting DSW et al.	2017	Cluster-bootstrap, biased-corrected, asymptotic 2-sided	Singapore National data	(Training + Testing images) 125189 + 71896
Kumar Nath and Dandapat (2013)	Malaya Kumar Nath et. al	2013	Multiscale ICA	DRIVE ARIA	DRIVE: 565 × 584pixels (40 images) Aria: 768 × 576 pixels (92 images)
Kumar Kar et al. (2019)	Mithun Kumar Kar et al	2019	Multiscale- Wavelet Decomposition	MESSIDOR, ARIA and DRIVE	512×512 pixels (ARIA: 129 images, DRIVE: 40 images)
Al-Hazaimeh et al. (2022)	Obaida M. Al-hazaimeh et al	2022	SVMGA	Kaggle	88702 images
Gharaibeh et al. (2018)	Nasr Gharaibeh et al	2018	SVMGA	DIARETDB1	89 images
Gharaibeh et al. (2021)	Nasr Gharaibeh et al	2021	Hybrid SVM NB Classifier	DIARETDB0, DIARETDB1	1500×1152 pixels (DIARETDB0: 130 images, DIARETDB1: 89 images)

(*Continued*)

Table 2. (Continued).

Reported in	Researchers	Year	Algorithm/Methodology used	Dataset used	Brief of Images from Dataset
Age-related Macular Degeneration (AMD)					
Abràmoff et al. (2008, 2013)	Abramoff et. al.	2008, 2013	Retrospective analysis done using non-mydriatic images, Iowa Detection programme	Messidor, AREDS	7689 quality images) 640×640 pixel size (Abràmoff et al. 2008), 1748 images (Abràmoff et al. 2013)
SinaFarsiu et al. (2014)	SinaFarsiu et. al	2014	AREDS classification	AREDS2 and A2A SD-OCT	1001×1001 pixels (38400 SDOCT images)
Chiu et al. (2015)	Stephanie et. al.	2015	kernel regression (KR)-based classification, graph theory and dynamic programming (GTDP) framework	Chiu_BOE 2014	110 B-scans
Deng et al. (2016)	Jingjing Deng et. al	2016	Gabor filtering, energy transformation, Random forests and SVM	Choroid OCT image dataset	420 images (512 × 512 × 1024 volume scan)
Burlina et al. (2017)	Philippe M. Burlina et. Al	2017	AlexNet (University of Toronto)DCNN model	AREDS	More than 130,000 images
Bogunovic et al. (2017)	Hrvoje Bogunovic et. al.	2017	Drusen regression	Private live data	128 B-scans (512×1024 pixels)
Venhuizen et al. (2018)	Freek G. Venhuizen et. al	2017	U-net network	EUGENDA	221 SD-OCT volumes(Receptive field: 572 × 572 pixels)
Keel et al. (2019)	Keel et. al.	2019	The deep convolution neural network	local dataset (from clinical setup of China)	56113 retinal images & additional 86,162 images
Hong et al. (2021)	Jiaxu Hong et. al	2021	Hierarchical Deep Learning Framework	EyePACS; Kaggle	7100 images
Ting et al. (2017)	Ting DSW et al.	2017	Cluster-bootstrap, biased-corrected, asymptotic 2-sided	Singapore National data	(Training + Testing images) 125189 + 71896
Cataract					
Gao et al. (2015)	Xinting Gao et. al	2015	Convolutional-Recursive Neural Networks	ACHIKO-NC	5378 images (anterior cortex of the ROI-148×148, the nucleus:148×296 and posterior cortex: 148 × 148)
Shah Junayed et al. (2019)	Masum Shah Junayed et. al	2017	CataractNet	ACHIKO-I	non-cataract and cataract images are 2067 and 2679 (RGB images: 224 × 224)
Imran et al. (2021)	Azhar Imran et. al	2021	hybrid CRNN (AlexNet, GoogLeNet, ResNet and VGGNet)	Data collected from Tongren Hospital, China	2048 images (3888×2592)
Glaucoma/Retinoblastoma					
RubinaSarki et al. (2021)	Rubina Sarki et al	2021	CNN	Messidor, DRISHTI-GS, Messidor-2 and GitHub's Retinal Dataset.	Messidor database-1200 Messidor-2–1,748 DRISHTI-GS Dataset-100 (224 × 224 pixels)
Ting et al. (2017)	Ting DSW et al.	2017	Cluster-bootstrap, biased-corrected, asymptotic 2-sided	Singapore National data	(Training + Testing images) 125189 + 71896
Hong et al. (2021)	Jiaxu Hong et al	2021	Hierarchical Deep Learning Framework	EyePACS; Kaggle	7100 images
Anand Deva Durai et al. (2021)	C. Anand Deva Durai et al	2021	Liner Predictive Decision based Median Filter (LPDMF), CNN	American Society of Retina specialists	29386 images
Madhusudhan et al. (2011)	Mishra Madhusudan et. al	2011	Image Processing (3-steps: Preprocessing-Segmentation-classification)	CDR Fundus images from www.opticdisc.org.	25 Images
Kumar Nath and Dandapat (2012)	Malaya Kumar Nath et. al	2012	Differential entropy and Wavelet Decomposition	DRIVE	144×144 pixels (54 images)
Elangovan and Malaya (2020)	Poonguzhali Elangovan et. al	2020	CNN	DRISHTI-GSI, RIM-ONE2, ORIGIA, LAG ACRIMA	DRISHTI-GSI :2896 × 1944 pixels (101 images) RIM-ONE2: 290 × 290to 1375 × 1654pixels (455 images) ORIGIA : 3072 × 2048pixels (650 images) LAG : 500 × 500pixels (4854 images) ACRIMA : 178 × 178to 1420 × 1420pixels (705 images)
Elangovan and Kumar Nath (2022)	Poonguzhali Elangovan et. al	2022	DCNN,SVM	DRISHTI-GS1, RIM-ONE2, ORIGIA, LAG ACRIMA	DRISHTI-GS1: 101 images ORIGIA: 650 images LAG: 4854 images ACRIMA: 705 images
Kar et al. (2023)	Mithun Kumar Kar et al	2022	MSR-Net, GAN	DRIVE, STARE, CHASE_DB1, HRF, ARIA, IOSTAR,RC-SLO	DRIVE:40 images, STARE: 81 images, HRF:45 images, ARIA: 120 images, IOSTAR: 30 images, RC-SLO: 40 vascular patch
Prajna and Nath (2022)	Prajna et al.	2022	U-NET	DRIVE, ARIA_d and MESSIDOR	DRIVE:40 images
Retinal Diseases					
Ravichandran et al. (2019)	Giritharan Ravichandran et. Al	2019	Gaussian Filter, CLAHE	RIPS, DRIVE (for normal eyes)	1440×2160x3 (RIPS: 120 images)

Table 3. Analysis of datasets considered by researchers.

	Diseases				
Datasets	DR	AMD	Cataract	Glaucoma/Retinoblastoma	Retinal Diseases
MESSIDOR	(Abràmoff et al. 2008, 2013), (Imani et al. 2015; Solanki et al. 2015; Dhara et al. 2015), (Gulshan et al. 2016), (Sil Kar and Maity 2017; Gargeya and Leng 2017; Shanthi and Sabeenian 2019), (Dorizzi et al. 2020), (Abdel Maksoud et al. 2022; Suman et al. 2023), (Kumar Kar et al. 2019)	(Abràmoff et al. 2008), (Abràmoff et al. 2013)		(RubinaSarki et al. 2021)	
Kaggle Dataset	(Pratt et al. 2016), (Lam et al. 2018), (Muhammad Saiful Islam and Abdullah 2018), (Leeza and Farooq 2019), (Li et al. 2018), (Qummar et al. 2019), (Long Zeng et al. 2019), (Zhang et al. 2022), (Al-Hazaimeh et al. 2022)	(Hong et al. 2021)		(Hong et al. 2021)	
DIARETDB	(Seoud et al. 2016), (Sil Kar and Maity 2017), (Dorizzi et al. 2020), (Sakshi Gunde and Gupta 2020), (Gharaibeh et al. 2018), (Gharaibeh et al. 2021)				
EyePACS	(Gulshan et al. 2016), (Abdel Maksoud et al. 2022)	(Hong et al. 2021)		(Hong et al. 2021)	
APTOS	(Abdel Maksoud et al. 2022), (Suman et al. 2023)				
IDRiD	(Abdel Maksoud et al. 2022)				
AREDS		(Abràmoff et al. 2008), (Abràmoff et al. 2013), (SinaFarsiu et al. 2017), (Burlina et al. 2017)			
Chiu_BOE 2014		(Chiu et al. 2015)			
A2A SD-OCT		(Abràmoff et al. 2013)			
ACHIKO			(Gao et al. 2015), (Shah Junayed et al. 2019)		
DRISHTI-GS (1/2)				(RubinaSarki et al. 2021), (Elangovan and Kumar Nath 2022)	
GitHub's Retinal Dataset				(RubinaSarki et al. 2021)	
RIPS					(Ravichandran et al. 2019)
DRIVE	(Kumar Kar et al. 2019)			(Kumar Nath and Dandapat 2012), (Kumar Nath and Dandapat 2013) (Kar et al. 2023)	(Ravichandran et al. 2019)
ORIGIA				(Elangovan and Malaya 2020), (Elangovan and Kumar Nath 2022)	
LAG				(Elangovan and Malaya 2020), (Elangovan and Kumar Nath 2022)	
ACRIMA				(Elangovan and Malaya 2020), (Elangovan and Kumar Nath 2022)	
RIM-ONE				(Elangovan and Malaya 2020), (Elangovan and Kumar Nath 2022)	
ARIA	(Kumar Kar et al. 2019)			(Kumar Nath and Dandapat 2013), (Kar et al. 2023)	
Local or private dataset or others	(Mohammad Alipour et al. 2012), (Esmaeili et al. 2014), (Rahim et al. 2016), (Gargeya and Leng 2017), (Gao et al. 2019), (Wang et al. 2019)	(Deng et al. 2016), (Bogunovic et al. 2017), (Bogunovic et al. 2017), (Venhuizen et al. 2018), (Keel et al. 2019)	(Imran et al. 2021), (Kar et al. 2023)	(Ting et al. 2017), (Anand Deva Durai et al. 2021), (Madhusudhan et al. 2011)	

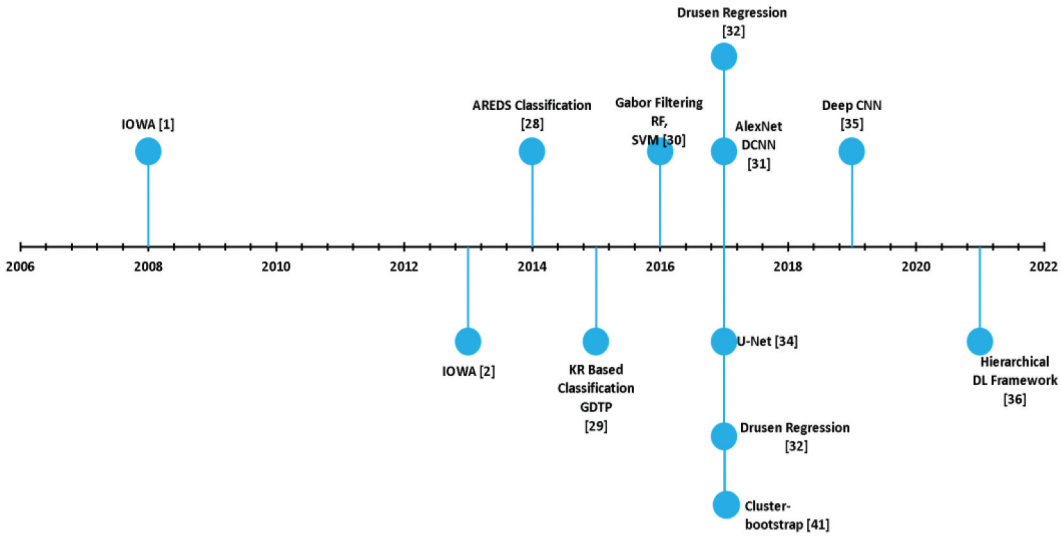

Figure 4. Time line chart for age-related macular degeneration (AMD).

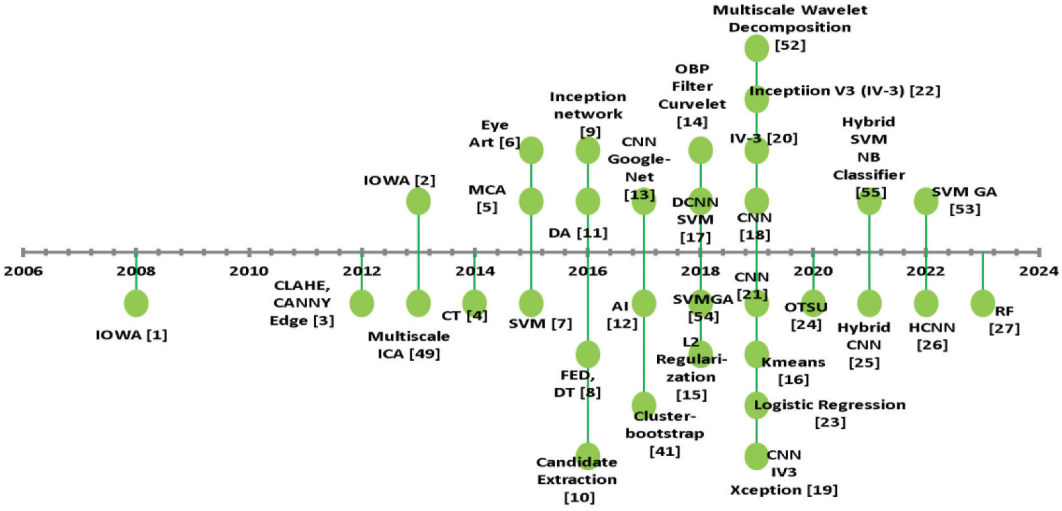

Figure 5. Timeline chart for diabetic retinopathy (DR).

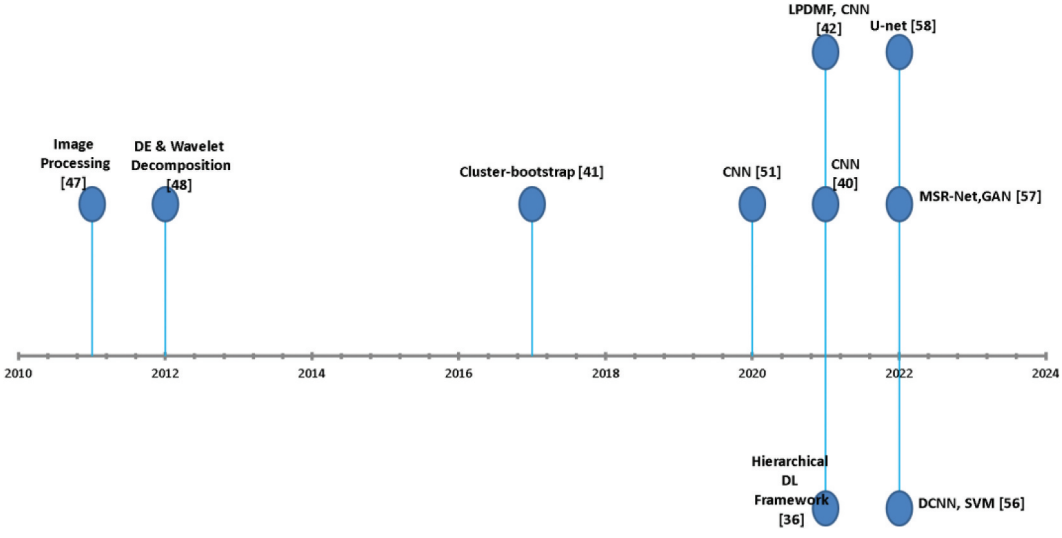

Figure 6. Timeline chart for glaucoma and retinoblastoma.

Table 4. Overview of methods for ophthalmic diseases detection with its scope for improvement.

Reported In	Diseases	Researchers	Year	Algorithm/ Methodology used	Concluding Remark	Scope of Improvement
Abdel Maksoud et al. (2022)	Diabetic Retinopathy	Eman AbdelMaksoud et. al	2022	Hybrid CNN (EyeNet model and DenseNet model)-CAD	Diagnosed normal and DR grades viz. mild, moderate and severe non-proliferative DR (NPDR) and proliferative DR (PDR)	need to focus on other diseases (AMD, Glaucoma) also on other imaging modalities and accuracy needs to be increased
SinaFarsiu et al. (2014)	AMD	Sina Farsiu et. al	2014	AREDS classification	Only detect AMD	Can improved disease progression and vision loss for AMD
Venhuizen et al. (2018)	AMD	Freek G. Venhuizen et. al	2017	U-net network	detect and segment IRC or cysts in SD-OCT Volumes	failed in intermediate level of AMD
Gao et al. (2015)	Cataract	Xinting Gao et. al	2015	Convolutional-Recursive Neural Networks	Detect only nuclear cataract	can improved performance in segmentation
Shah Junayed et al. (2019)	Cataract	Masum Shah Junayed et. al	2017	CataractNet	Only cataract detection	• Grading can be done • Identification of the exact disease location • categorise the three types of age-related cataracts
Imran et al. (2021)	Cataract	Azhar Imran et. al	2021	hybrid CRNN (AlexNet, GoogLeNet, ResNet and VGGNet)	better performance for the 3 classes such as normal, mild and moderate	Severity grade can improve classification accuracy for larger dataset
RubinaSarki et al. (2021)	DME, DR, & Glaucoma	Rubina Sarki et al	2021	CNN	Only identified mild to moderate grading of each disease	Severity of diseases can be identified.
Ting et al. (2017)	DR, Glaucoma & AMD	Ting DSW et al.	2017	Cluster-bootstrap, biased-corrected, asymptotic 2-sided	high sensitivity and specificity for identifying DR, AMD and Glaucoma	Other types of AMD can be identified
Elangovan and Malaya (2020)	Glaucoma	Poonguzhali Elangovan et. al	2020	CNN	Attained high level classification accuracy	need to focus on other diseases
Gharaibeh et al. (2021)	Diabetic Retinopathy	Nasr Gharaibeh et al	2021	Hybrid SVM NB Classifier	Attained better performance for optic disc classification and localisation	Can improve accuracy level to detect spots of cotton wool and exudates

Table 5. Analysis of parameter metrics considered by researchers.

Parameter Metrics	Disease wise Reported In			
	DR	AMD	Glaucoma	Retinal Diseases
Sensitivity	(Abràmoff et al. 2008), (Abràmoff et al. 2013), (Mohammad Alipour et al. 2012), (Esmaeili et al. 2014), (Imani et al. 2015), (Solanki et al. 2015), (Rahim et al. 2016), (Gulshan et al. 2016), (Pratt et al. 2016), (Gargeya and Leng 2017), (Sil Kar and Maity 2017), (Muhammad Saiful Islam and Abdullah 2018), (Leeza and Farooq 2019), (Li et al. 2018), (Dorizzi et al. 2020), (Sakshi Gunde and Gupta 2020), (Zhang et al. 2022), (Abdel Maksoud et al. 2022), (Suman et al. 2023), (Kumar Kar et al. 2019), (Al-Hazaimeh et al. 2022), (Gharaibeh et al. 2018), (Gharaibeh et al. 2021)	(Abràmoff et al. 2008), (Abràmoff et al. 2013), (SinaFarsiu et al. 2014), (Keel et al. 2019)	(Madhusudhan et al. 2011) (Elangovan and Malaya 2020), (Kar et al. 2023), (Kar et al. 2021; Prajna and Nath 2022)	(Ravichandran et al. 2019)
Specificity	(Abràmoff et al. 2008), (Abràmoff et al. 2013), (Mohammad Alipour et al. 2012), (Esmaeili et al. 2014), (Imani et al. 2015), (Solanki et al. 2015), (Rahim et al. 2016), (Gulshan et al. 2016), (Gargeya and Leng 2017), (Sil Kar and Maity 2017), (Muhammad Saiful Islam and Abdullah 2018), (Leeza and Farooq 2019), (Li et al. 2018), (Sakshi Gunde and Gupta 2020), (Zhang et al. 2022), (Abdel Maksoud et al. 2022), (Suman et al. 2023), (Kumar Kar et al. 2019), (Al-Hazaimeh et al. 2022), (Gharaibeh et al. 2018), (Gharaibeh et al. 2021)	(Abràmoff et al. 2008), (Abràmoff et al. 2013), (SinaFarsiu et al. 2017), (Keel et al. 2019)	(Madhusudhan et al. 2011) (Elangovan and Malaya 2020), (Prajna and Nath 2022)	(Ravichandran et al. 2019)
Accuracy	(Rahim et al. 2016), (Pratt et al. 2016), (Sil Kar and Maity 2017), (Leeza and Farooq 2019), (Li et al. 2018), (Shanthi and Sabeenian 2019), (Gao et al. 2019), (Zhang et al. 2022), (Abdel Maksoud et al. 2022), (Suman et al. 2023), (Kumar Kar et al. 2019), (Al-Hazaimeh et al. 2022), (Gharaibeh et al. 2018), (Gharaibeh et al. 2021)	(Keel et al. 2019), (Hong et al. 2021)	(Kumar Nath and Dandapat 2012) (Elangovan and Malaya 2020), (Elangovan and Kumar Nath 2022), (Kar et al. 2023), (Prajna and Nath 2022)	(Ravichandran et al. 2019)
AUC	(Dhara et al. 2015), (Muhammad Saiful Islam and Abdullah 2018), (Al-Hazaimeh et al. 2022)	(SinaFarsiu et al. 2014), (Bogunovic et al. 2017), (Bogunovic et al. 2017), (Hong et al. 2021)		
HEM ROC value	(Seoud et al. 2016), (Dorizzi et al. 2020)			
Kappa	(Long Zeng et al. 2019)			
2/3/4-ary classification	(Lam et al. 2018), (Qummar et al. 2019)			
Misclassification error	(Rahim et al. 2016)			
Severity Prediction	(Wang et al. 2019)			
Overall mean Dice coefficient		(Chiu et al. 2015)		
Mean central macular thickness		(Deng et al. 2016)		
Segmentations		(Deng et al. 2016)		
Thickness difference		(Chiu et al. 2015)		
API	(Kumar Nath and Dandapat 2013)			
Common Test Values	(Kumar Nath and Dandapat 2013)			
Equal Error Rate	(Kumar Kar et al. 2019)			(Ravichandran et al. 2019)
Conformity coefficient				(Ravichandran et al. 2019)
Sensibility	(Kumar Kar et al. 2019)		(Prajna and Nath 2022)	(Ravichandran et al. 2019)
Jaccord's Coefficient			(Prajna and Nath 2022)	(Ravichandran et al. 2019)
F1 Score			(Kar et al. 2023)	(Ravichandran et al. 2019)
Precision			(Elangovan and Malaya 2020), (Kar et al. 2023)	
Intersection of Union			(Kar et al. 2023)	
Dice coefficient			(Prajna and Nath 2022)	(Ravichandran et al. 2019)

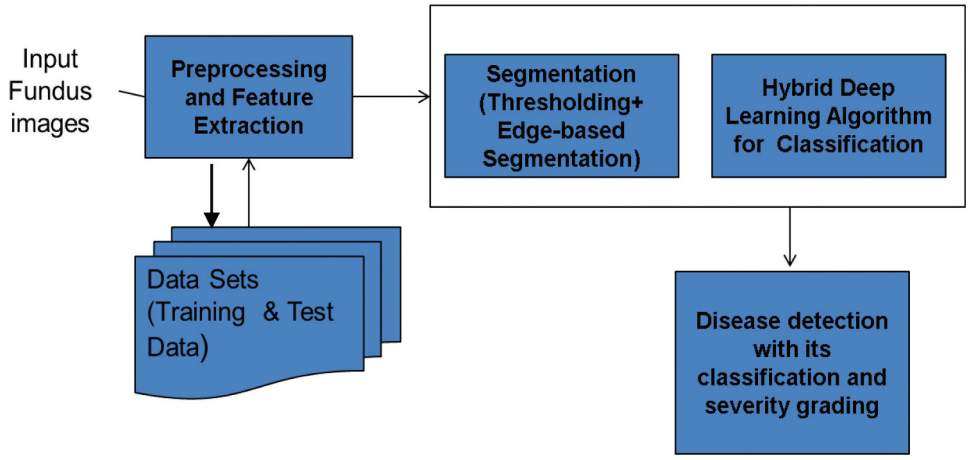

Figure 7. Proposed system architecture.

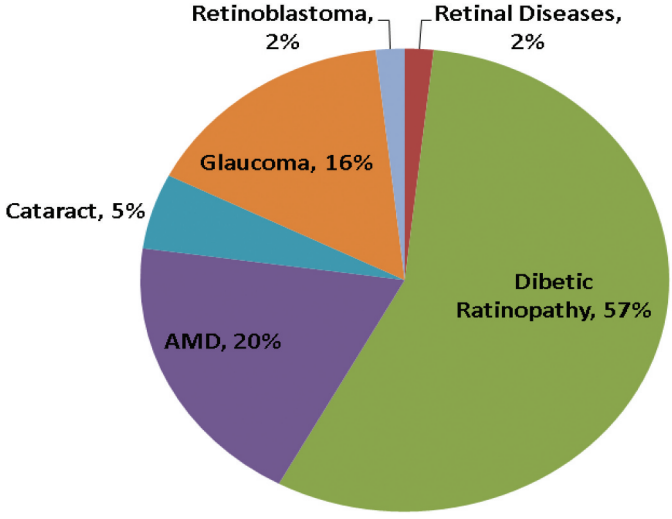

Figure 8. Analysis of diseases considered by researchers.

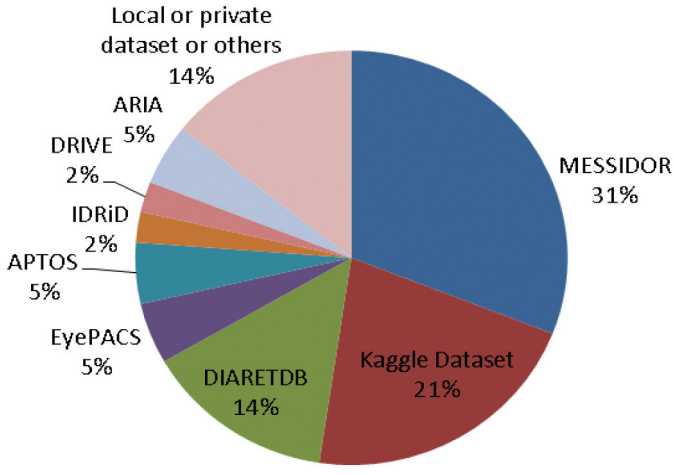

Figure 10. Analysis of datasets used by researchers in DR.

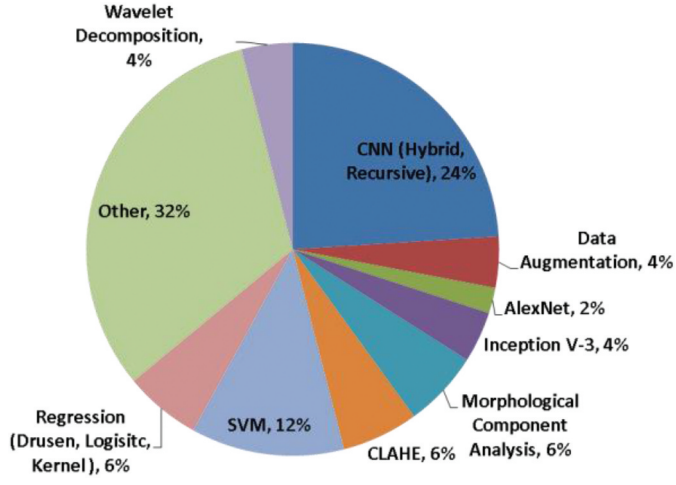

Figure 9. Analysis of techniques used by researchers.

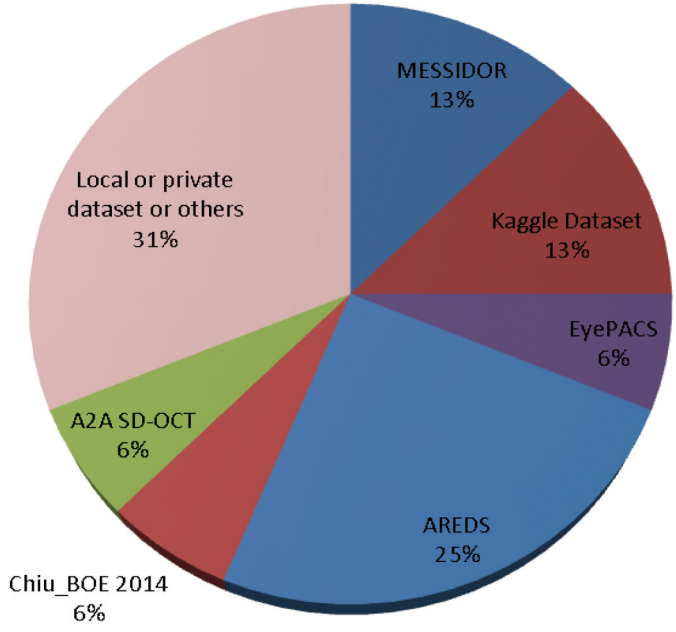

Figure 11. Analysis of datasets used by researchers in AMD.

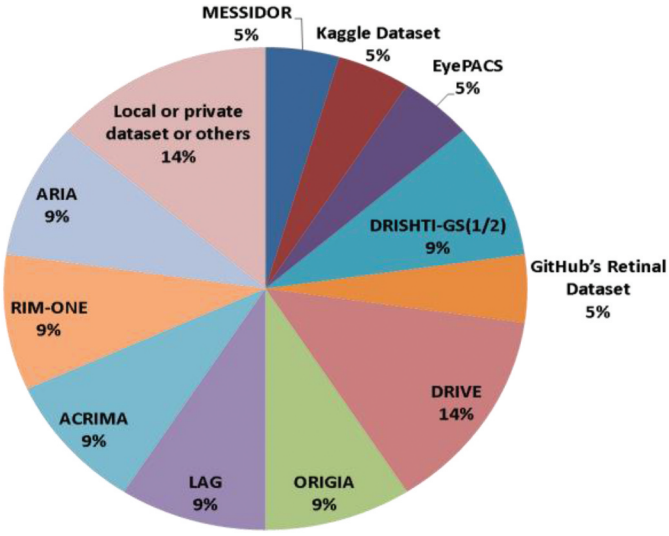

Figure 12. Analysis of datasets used by researchers in glaucoma and retinoblastoma.

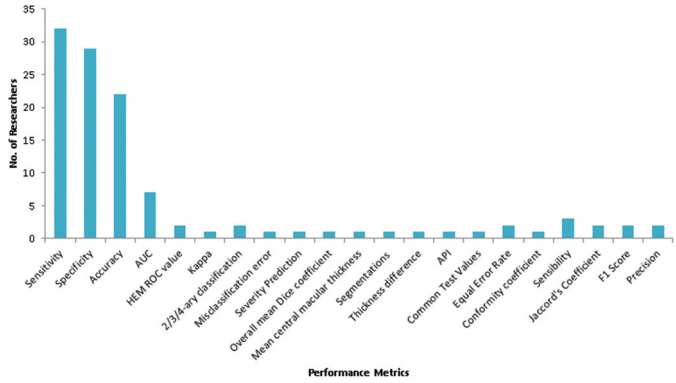

Figure 13. Analysis of performance metrics considered by researchers.

review stated that researchers used standard datasets mostly DIARETDB, AREDS, EyePACS, Kaggle, Messidor and Other & local/private dataset 14%, 7%, 7%, 21%, 28% and 28%, respectively. From the analysis, it has been observed that most of researchers used CNN techniques (24%). Graphical representation of this study is shown in Figures 8–15.

As this paper discussed some selective and innovative methods to detect the ophthalmic diseases with their scope for the improvement, some challenges need to be addressed. First challenge is that disease is to detect at early stage. Second task is that to develop a single system together to address various ophthalmic diseases at early stage diagnosis. Lastly, the other eye disease viz. retinopathy of prematurity, thyroid eye disease, etc. can be considered for the future research work due to less consideration for the study.

9. Summary

This review paper provides a comprehensive and up-to-date overview of ophthalmic diseases, encompassing their epidemiology, risk factors, diagnostic challenges and innovative solutions. By addressing these insights, challenges and innovations, we can advance our efforts to cut the global encumbrance of ophthalmic diseases and enhance the quality of life for affected individuals. Moreover, this study found that 28% of researchers utilised the publicly available Messidor dataset and 24% employed CNN techniques to address ophthalmic diseases, with 57% focusing on diabetic retinopathy. Despite the existence of effective methods, there is still scope for improvement in systems for detecting multiple ophthalmic diseases. So to overcome the limitation of existing system, our proposed system aims to enhance detection and

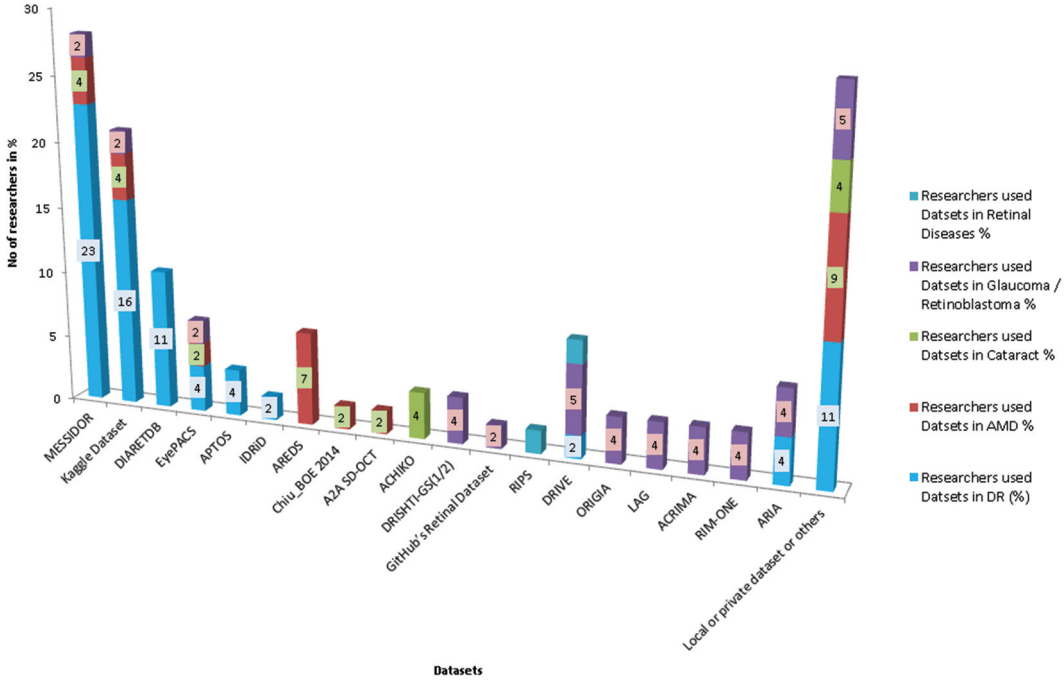

Figure 14. Analysis of datasets used by researchers (%) in various ophthalmic diseases.

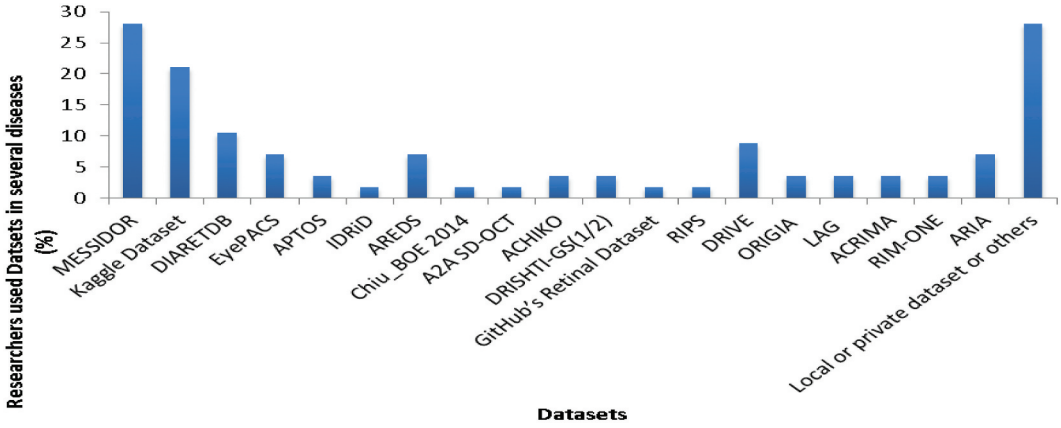

Figure 15. Overall datasets used by researchers in (%).

classification of various ophthalmic diseases and their severity grades within a single framework.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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