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# Optical Remote Sensing and Ophthalmic Diseases: A Survey

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## Abstract

Optical remote sensing technologies, including satellite imaging and advanced spectrometry, are increasingly pivotal in ophthalmic health and environmental monitoring. This interdisciplinary survey examines the integration of these technologies to assess their impact on eye health, particularly in diagnosing ophthalmic diseases and understanding environmental influences. Recent advancements in imaging, machine learning, and AI have enhanced the precision of remote sensing data, facilitating early diagnosis and improved management of conditions like diabetic retinopathy and macular degeneration. The survey underscores the significance of lighting environments and atmospheric conditions in influencing ocular health, advocating for comprehensive monitoring systems to mitigate adverse effects. Despite technological progress, challenges persist in data handling, communication, and integration of diverse datasets. Future research should focus on developing higher resolution sensors, optimizing AI models for remote sensing applications, and refining image processing techniques to overcome these barriers. Ultimately, the continued evolution of optical remote sensing technologies promises significant advancements in both ophthalmic health management and environmental monitoring, contributing to better health outcomes and effective environmental stewardship.

## 1 Introduction

### 1.1 Importance of Environmental Monitoring

Environmental monitoring plays a critical role in understanding and managing ophthalmic diseases by providing essential data on outdoor conditions that directly affect eye health. Real-time monitoring is particularly valuable, offering insights into air quality, weather, and other factors that may exacerbate ophthalmic issues [1]. With over 2.2 billion individuals globally affected by vision impairment and major ophthalmic diseases, the necessity for such monitoring is underscored, especially in regions where eye care services are insufficient [2].

The integration of IoT systems into environmental monitoring is vital, particularly in rural areas where power constraints and harsh conditions are prevalent [3]. Advanced technologies, such as dual-band plasmonic absorbers, enhance sensing capabilities in near-infrared (NIR) and mid-infrared (MIR) regions, overcoming limitations of existing methods and improving insights into environmental impacts on eye health [4].

Research has emphasized the interaction of atmospheric conditions with light, which can induce optical distortions influenced by temperature and wind speed, highlighting the need for comprehensive monitoring systems [5]. The increasing frequency of natural disasters, such as earthquakes and typhoons, further illustrates the necessity for robust environmental monitoring systems to mitigate potential health impacts [6].

Addressing the lack of time synchronization protocols in environmental monitoring networks is crucial for enhancing the accuracy and reliability of data collection [7]. As eye diseases continue to be

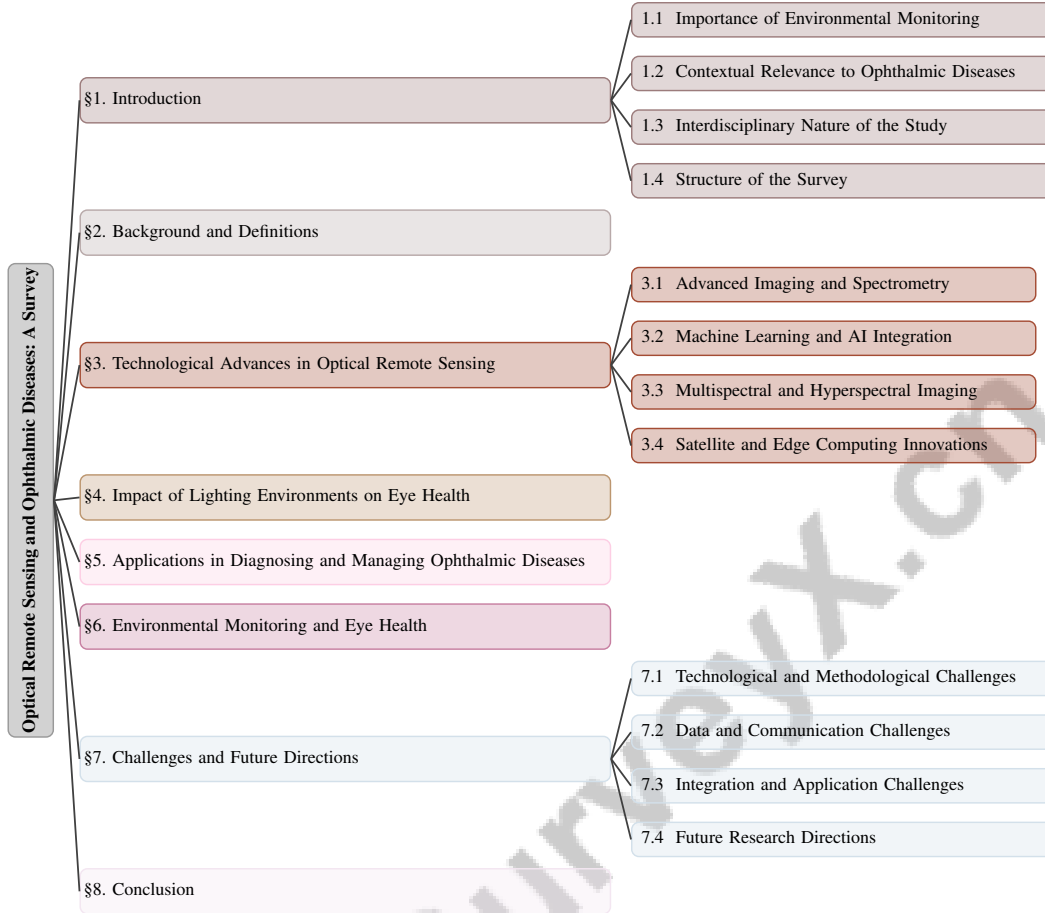


Figure 1: chapter structure

a global health concern affecting economic growth, improved diagnostic methods and comprehensive environmental monitoring are essential for effective disease management and prevention [8].

## 1.2 Contextual Relevance to Ophthalmic Diseases

The relationship between environmental factors and ophthalmic diseases is critical for advancing diagnostic and management strategies in eye care. Environmental conditions, including artificial lighting and atmospheric influences, significantly impact eye health, necessitating comprehensive monitoring systems to mitigate health risks. Artificial lighting, prevalent in various environments, has been linked to ecological and health consequences, underscoring the need for integrated environmental management, especially in rural settings where resource fragmentation complicates decision-making [3]. The challenge of accurately measuring environmental parameters, such as temperature and wind speed, is exacerbated by atmospheric turbulence affecting optical fields, emphasizing the need for precise monitoring [5].

Ophthalmic diseases, a leading cause of blindness affecting approximately 2.2 billion people, necessitate early detection through fundus examination. However, the complexity of multi-label classifications in imbalanced datasets, such as ODIR-5K, presents significant challenges [9]. The subjective nature of eye disease diagnosis from fundus images further complicates the connection between environmental factors and ophthalmic diseases, highlighting the urgent need for advancements in diagnostic methodologies [8]. Additionally, the detection limitations of thin film biosensors due to noise interference hinder their effectiveness in diagnostics and environmental monitoring, indicating a critical area for technological improvement [10].

The pathogenesis of ophthalmic diseases, such as age-related macular degeneration and diabetic retinopathy, is influenced by environmental factors. Innovative treatment approaches, including in-

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jectable hydrogels, present promising therapeutic avenues [11]. Understanding the role of angiogenic factors and mechanisms of angiogenesis is crucial, with clinical applications of anti-angiogenic drugs offering significant therapeutic potential [12]. These insights collectively highlight the profound impact of environmental conditions on eye health, establishing a foundation for the survey of optical remote sensing technologies in ophthalmology.

### 1.3 Interdisciplinary Nature of the Study

The study of optical remote sensing in ophthalmic diseases exemplifies a quintessential interdisciplinary approach, integrating principles and technologies from optical sciences, ophthalmology, and environmental science. The incorporation of advanced technologies, such as the EyeCLIP visual-language foundation model and visual question answering (VQA) systems, is essential for addressing the complex challenges associated with ophthalmic conditions influenced by various environmental factors. These innovations facilitate the analysis of multimodal ophthalmic images, promoting early detection and diagnosis of diseases like glaucoma, macular degeneration, and diabetic retinopathy. The development of injectable hydrogels for targeted drug delivery represents a promising approach to enhance treatment efficacy, underscoring the need for collaboration between medical professionals and AI experts to improve patient outcomes in ophthalmology [13, 14, 11]. The deployment of optical remote sensing technologies, including satellite imaging and advanced spectrometry, provides critical insights into environmental conditions affecting eye health, bridging gaps between environmental monitoring and medical diagnostics.

In ophthalmology, integrating remote sensing technologies with advanced machine learning methods, such as VQA and Self-Supervised Vision Transformers (SSVT), enables non-invasive diagnostic approaches that significantly enhance the accuracy and efficiency of eye disease detection. These innovative techniques leverage multimodal ophthalmic images and large language models to improve diagnostic capabilities while addressing challenges related to the lack of annotated datasets and the need for comprehensive evaluation methods. By facilitating objective assessments and reducing the burden on medical professionals, these technologies hold great promise for advancing eye care, particularly in resource-limited regions [13, 8]. The integration of machine learning and AI further augments these capabilities by enabling sophisticated image analysis and pattern recognition, crucial for early diagnosis and management of conditions such as age-related macular degeneration and diabetic retinopathy. These technological advancements underscore the vital role of interdisciplinary collaboration in developing innovative solutions for complex health issues.

Environmental science significantly contributes to this interdisciplinary framework by providing a comprehensive understanding of ecological and atmospheric variables impacting eye health. The interaction between optical fields and atmospheric conditions, including turbulence and light distortion, necessitates precise environmental monitoring to mitigate potential adverse effects on vision [5]. The utilization of IoT systems in environmental data collection enhances the reliability and scope of monitoring efforts, particularly in remote or resource-limited settings [3].

Collectively, these interdisciplinary efforts foster a holistic approach to understanding and managing ophthalmic diseases, leveraging the strengths of each field to improve health outcomes and advance scientific knowledge. The integration of optical remote sensing, ophthalmology, and environmental science significantly enhances both diagnostic and therapeutic approaches in eye health and improves environmental monitoring capabilities. This multidisciplinary synergy facilitates the development of innovative technologies, such as machine learning models for analyzing multimodal ophthalmic images and improved remote sensing techniques for assessing light pollution and its health effects. By leveraging methodologies like VQA and novel optical sensor designs, researchers are paving the way for breakthroughs that address the complexities of eye diseases and environmental changes, ultimately leading to more effective interventions and monitoring strategies [15, 16, 13, 14, 5].

### 1.4 Structure of the Survey

This survey is structured to provide a comprehensive exploration of the integration of optical remote sensing technologies in the context of ophthalmic diseases and environmental monitoring. The paper begins with an **Introduction**, which underscores the importance of optical remote sensing in understanding and managing ophthalmic diseases, highlighting the interdisciplinary nature of the

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study involving satellite imaging, lighting environments, and eye health. This sets the stage for the subsequent sections by establishing the foundational context and relevance.

In **Section 2: Background and Definitions**, key concepts and technologies such as optical remote sensing, satellite imaging, and lighting environments are defined, discussing their relevance to eye health and the diagnosis of ophthalmic diseases. This section aims to equip the reader with the necessary technical understanding to appreciate the subsequent discussions.

**Section 3: Technological Advances in Optical Remote Sensing** delves into recent advancements in optical remote sensing technologies, exploring their applications in environmental monitoring and adaptation for ophthalmic purposes. Subsections cover advancements in imaging, spectrometry, machine learning, AI integration, multispectral and hyperspectral imaging, and innovations in satellite and edge computing.

**Section 4: Impact of Lighting Environments on Eye Health** investigates the influence of various lighting conditions on ocular health, with a particular focus on their correlation with the prevalence and progression of ophthalmic diseases such as age-related macular degeneration, glaucoma, and diabetic retinopathy. This section highlights how factors like light pollution and the transition to LED lighting may contribute to these conditions, emphasizing the need for further research to understand the mechanisms behind these relationships and to develop effective preventive strategies [15, 17, 13, 11, 14]. It discusses the challenges posed by environmental uncertainty and the role of technological integration in enhancing monitoring capabilities.

**Section 5: Applications in Diagnosing and Managing Ophthalmic Diseases** focuses on the practical applications of optical remote sensing and satellite imaging in the diagnosis and management of ophthalmic diseases. The article provides a comprehensive overview of various case studies and examples illustrating the successful implementation of advanced technologies, such as Visual Question Answering (VQA) in ophthalmology, end-to-end Internet of Things (IoT) infrastructures for environmental monitoring, and innovative systems like EyeCLIP for multi-modal ophthalmic image analysis, showcasing their effectiveness in real-world applications across diverse fields [13, 18, 14, 3].

In **Section 6: Environmental Monitoring and Eye Health**, the broader implications of environmental monitoring on eye health are explored. The section discusses how satellite imaging and optical remote sensing contribute to understanding environmental factors affecting eye health.

**Section 7: Challenges and Future Directions** highlights the significant obstacles faced in integrating optical remote sensing technology with ophthalmic health monitoring, particularly in the context of diabetic retinopathy screening. This section also explores innovative research opportunities and future pathways in this interdisciplinary field, emphasizing the need for advanced sensor technologies that can improve the accuracy and efficiency of health monitoring. It discusses the implications of emerging tools such as artificial intelligence and teleophthalmology, which could enhance screening strategies, as well as the potential for optical remote sensing to contribute to broader health assessments, including cardiovascular and cognitive risk evaluations [15, 19].

In **Section 8: Conclusion**, the survey synthesizes the principal findings, emphasizing the critical role of optical remote sensing technologies in both ophthalmic health diagnostics and environmental monitoring. It highlights how advancements in remote sensing can enhance our understanding of light pollution's effects on health and the environment, while also identifying specific areas for future research, including the development of higher-resolution sensors and multimodal approaches that integrate various imaging techniques to improve diagnostic accuracy and environmental assessments [20, 15, 21, 16, 13]. The following sections are organized as shown in Figure 1.

## 2 Background and Definitions

### 2.1 Optical Remote Sensing Technologies

Optical remote sensing technologies utilize light properties across various wavelengths to capture high-resolution imagery, facilitating environmental monitoring and enhancing ophthalmic diagnostics [22, 20, 23]. These technologies, through space-borne, airborne, and ground-based observations, provide a comprehensive view of environmental changes impacting eye health. Advanced imaging systems employing multi-temporal and multi-spectral data fusion improve the accuracy of remote

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sensing data [24]. Plasmonic structures, such as silver nanostructures on metal plates, enhance sensing in the NIR and MIR regions [4].

In ophthalmology, these technologies, including clustering algorithms like Fuzzy C-Means (FCM), facilitate retinal image analysis for early disease diagnosis. Non-invasive techniques such as hyperspectral NIR imaging and phase-sensitive optical coherence tomography enable detailed analysis of ocular structures, aiding in early detection of conditions like glaucoma and diabetic retinopathy [17, 10, 16, 25, 26].

Optical remote sensing also significantly contributes to environmental monitoring, particularly in land cover classification and assessing ecological impacts, including light pollution [15, 27, 23]. Earth Observation systems like MODIS and Sentinel provide essential data for tracking environmental changes. Machine learning advancements, such as Vision Graph Neural Networks (ViG), improve land-use monitoring and image classification, enabling timely responses to environmental changes [15, 27, 23]. Challenges like cloud coverage necessitate innovations in imaging techniques and data processing strategies, such as the ORSim detector and mid-infrared optical signal conversion [28, 29, 30].

Recent advancements in optical remote sensing, particularly regarding night light emissions and image resolution enhancement, underscore their role in environmental monitoring and ophthalmic diagnostics. These technologies facilitate urban mapping, light pollution assessment, and environmental change monitoring, emphasizing the need for innovative imaging techniques and algorithms [15, 21, 23, 16].

## **2.2 Satellite Imaging and Environmental Monitoring**

Satellite imaging is integral to environmental monitoring, offering high-resolution data crucial for assessing conditions impacting eye health. The integration of satellite imagery with monitoring systems enhances our understanding of land use patterns, urbanization, and climate change [15, 21, 16, 27, 31]. Advanced technologies like the Ocean Color Monitor-3 and multi-resolution fusion techniques improve image resolution, enabling accurate environmental assessments. Night light emissions data provide insights into human activity and environmental consequences, linking these to public health outcomes.

Cloud cover remains a challenge in satellite imaging, particularly in coastal areas. Recommender system-inspired methods and advanced image processing techniques, such as WavCycleGAN, enhance data quality by addressing these challenges [32, 33]. Satellite imaging excels in capturing data in the visible spectral range, crucial for monitoring artificial lighting conditions affecting eye health [15].

Despite limitations in spatial and temporal resolution, innovative methods like IoT-based monitoring systems enhance capabilities by integrating with satellite imagery [1]. Satellite imagery is vital for disaster response, providing essential data for managing flooded regions, though challenges in automatic identification necessitate improved data processing techniques [34]. Comprehensive environmental monitoring solutions that integrate various sensor data into cloud-based platforms enhance the utility of satellite imagery for effective management [3].

## **2.3 Lighting Environments and Eye Health**

Lighting environments significantly affect eye health, with factors such as intensity, duration, and spectrum of exposure playing crucial roles. Artificial lighting, prevalent in urban settings, disrupts circadian rhythms and contributes to eye strain, necessitating studies on its ecological and health impacts [3]. Blue light exposure from digital screens and LED lighting has been linked to retinal damage and age-related macular degeneration, emphasizing the need for monitoring and managing exposure [12].

The interaction between lighting and atmospheric conditions, such as turbulence, can lead to optical distortions affecting vision quality [5]. In rural areas, monitoring challenges due to resource limitations can be addressed by integrating IoT-based systems, facilitating real-time data collection on lighting conditions [1].

The complex relationship between lighting environments and eye health involves various environmental and technological factors. Advances in remote sensing technologies, higher-resolution night light sensors, and interdisciplinary approaches like Visual Question Answering (VQA) and multi-modal models such as EyeCLIP, enhance our understanding of artificial lighting's impact on health and improve early detection and treatment of eye conditions [15, 17, 13, 11, 14]. This interdisciplinary approach is vital for advancing our understanding of lighting effects on ocular health and developing comprehensive eye care solutions.

In recent years, the field of optical remote sensing has witnessed significant technological advancements that have transformed both environmental monitoring and medical diagnostics. The integration of various innovative techniques has not only enhanced the capabilities of remote sensing but also broadened its applications across different domains. Figure 2 illustrates the hierarchical structure of these technological advances, highlighting key innovations in advanced imaging and spectrometry, machine learning and AI integration, multispectral and hyperspectral imaging, as well as satellite and edge computing. Each category is meticulously divided into specific advancements and applications, showcasing the profound impact these technologies have on fields such as environmental monitoring and ophthalmic diagnostics. This structured overview not only provides clarity on the interrelations among different technological components but also emphasizes the ongoing evolution of remote sensing methodologies.

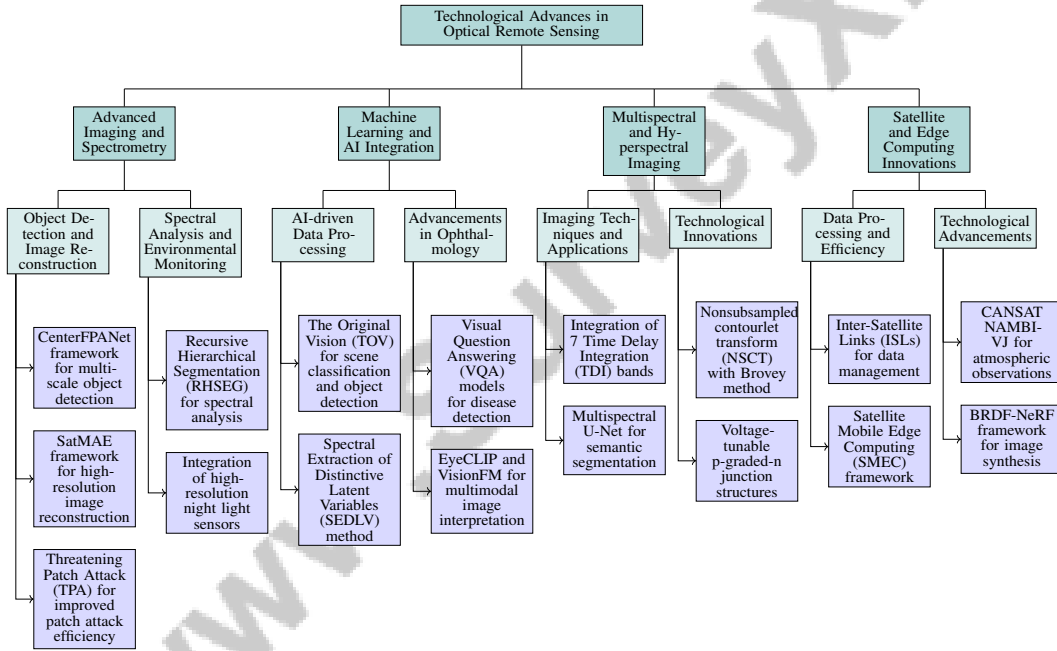


Figure 2: This figure illustrates the hierarchical structure of technological advances in optical remote sensing, highlighting key innovations in advanced imaging and spectrometry, machine learning and AI integration, multispectral and hyperspectral imaging, and satellite and edge computing. Each category is further divided into specific advancements and applications, showcasing the impact on environmental monitoring and ophthalmic diagnostics.

### 3 Technological Advances in Optical Remote Sensing

#### 3.1 Advanced Imaging and Spectrometry

Recent advancements in imaging and spectrometry have significantly bolstered optical remote sensing, enhancing its application in environmental monitoring and ophthalmic diagnostics. As illustrated in Figure 3, key methods and frameworks in object detection, hyperspectral imaging, and remote sensing enhancements are highlighted, showcasing the breadth of innovations in this field. The CenterFPANet framework exemplifies progress in object detection, utilizing multi-scale features to improve environmental monitoring [35]. In hyperspectral imaging, the Recursive Hierarchical

Segmentation (RHSEG) algorithm employs agglomerative hierarchical clustering to facilitate detailed spectral analysis, essential for tracking environmental changes and ocular health [36]. The SatMAE framework, a self-supervised learning model using masked autoencoders, enhances high-resolution image reconstruction by addressing the complexities of temporal and multi-spectral satellite images through independent masking and positional encodings [24]. Additionally, the Threatening Patch Attack (TPA) method improves patch attack efficiency while maintaining visual quality, integrating First-Order Difference (FOD) and Bounding Box Drifting Loss (BDL) [37]. These innovations collectively refine remote sensing analytical capabilities. The integration of high-resolution night light sensors and open-vocabulary object detection systems is crucial for enhancing remote sensing accuracy, facilitating a deeper understanding of environmental factors affecting eye health, such as light pollution [15, 20, 38].

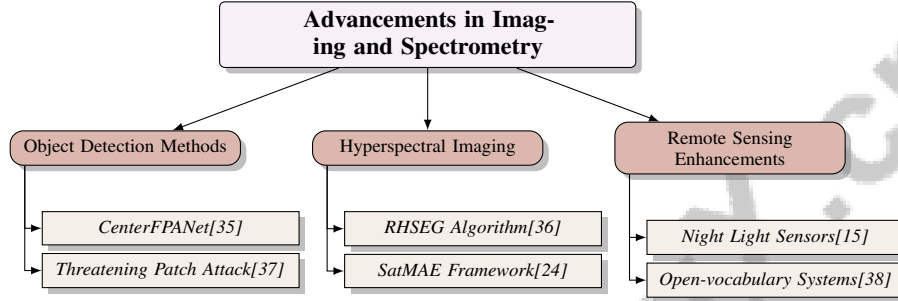


Figure 3: This figure illustrates recent advancements in imaging and spectrometry, highlighting key methods and frameworks in object detection, hyperspectral imaging, and remote sensing enhancements.

### 3.2 Machine Learning and AI Integration

The incorporation of machine learning (ML) and artificial intelligence (AI) into optical remote sensing has revolutionized the analysis of complex datasets, significantly boosting environmental monitoring and ophthalmic diagnostics. Self-supervised learning models, like The Original Vision (TOV), utilize large volumes of unlabeled data for scene classification and object detection, while multiscale methods enhance image captioning accuracy [23, 20, 22, 16]. AI-driven methodologies have markedly improved data processing capabilities, enabling more precise analyses. The Spectral Extraction of Distinctive Latent Variables (SEDLV) method employs graph-based techniques to analyze connectivity differences, enhancing spectral feature extraction for environmental monitoring and ophthalmic diagnostics [16]. The SatMAE framework exemplifies AI application, enhancing satellite data representation learning through temporal and spectral encodings [24]. Machine learning also optimizes adversarial attack methods like TPA, enhancing object detection in optical imagery by employing FOD for sub-patch selection and BDL for refining adversarial examples [37]. Additionally, integrating Orbital Angular Momentum (OAM) mode decomposition with machine learning accelerates environmental change detection, underscoring AI's transformative potential in optical remote sensing [5]. AI methodologies are pivotal for advancing remote sensing technologies, particularly in ophthalmology, where innovations like Visual Question Answering (VQA) and models such as EyeCLIP and VisionFM are revolutionizing multimodal image interpretation, leveraging extensive datasets to improve disease detection and diagnosis [13, 2, 14].

### 3.3 Multispectral and Hyperspectral Imaging

Multispectral and hyperspectral imaging are essential in remote sensing, providing detailed spectral information crucial for environmental monitoring and ophthalmic applications. These techniques capture data across a wide range of spectral bands, enhancing material identification and enabling comprehensive environmental condition assessments by capturing distinct spectral signatures [39, 16]. Multispectral imaging typically captures data across a limited number of broad spectral bands, while hyperspectral imaging collects data over hundreds of narrow bands, facilitating diverse applications such as land cover classification and mineral exploration. Recent advancements, including the integration of 7 Time Delay Integration (TDI) bands, have improved multispectral capture efficiency, enabling simultaneous acquisition across multiple bands [40]. Innovations like the Multispectral

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U-Net (MU-Net) enhance semantic segmentation of satellite imagery by modifying conventional architectures to leverage multispectral data, while the SatMAE framework optimizes performance through unsupervised pre-training techniques [24, 20, 41, 42, 33]. The nonsubsampling contourlet transform (NSCT) combined with the Brovey method has also improved image fusion quality by preserving spatial and spectral information. Hyperspectral imaging provides granular insights into spectral properties, enabling detection of subtle differences in material composition. The parallelization of the RHSEG algorithm has enhanced processing speed, achieving significant speedups in hybrid configurations for efficient classification of hyperspectral images [36]. Innovations such as voltage-tunable p-graded-n junction structures facilitate continuous spectral reconstruction, highlighting advancements in spectral imaging technologies tailored for remote sensing applications [43, 16]. Multispectral and hyperspectral imaging are indispensable in remote sensing, supporting applications from environmental monitoring to ophthalmic diagnostics. The continuous advancement of technologies like multi-modal ophthalmic image analysis is crucial for understanding Earth's surface and its environmental factors. These innovations enable early detection of eye diseases through integrated clinical data and monitor light pollution's effects on health, including ocular health, thus fostering better management of environmental influences [15, 14].

### 3.4 Satellite and Edge Computing Innovations

Advancements in satellite and edge computing technologies have significantly enhanced remote sensing capabilities, improving data acquisition, processing, and analysis. Inter-Satellite Links (ISLs) enable Low Earth Orbit (LEO) satellites to collaboratively manage extensive data generated during real-time Earth observation, reducing congestion and enhancing processing efficiency. Techniques like self-supervised learning and contrastive learning optimize satellite image segmentation and classification, minimizing the need for extensive labeled datasets while maintaining high accuracy [44, 45, 46]. The Satellite Mobile Edge Computing (SMEC) framework optimizes data distribution and compression, allowing for higher image throughput and reduced energy consumption, demonstrating edge computing's potential in satellite data processing [45]. Innovations like the CANSAT NAMBI-VJ, which integrates a gyroscope for stabilization and employs a spill-hole parachute for controlled descent, improve data accuracy during atmospheric observations [47]. The BRDF-NeRF framework represents a significant advancement in image synthesis and digital surface modeling, utilizing neural radiance fields to generate high-quality models from limited satellite images [48]. On-board processing capabilities in CubeSats, particularly in flood detection applications, exemplify edge computing's advantages by minimizing data transmission needs and enhancing disaster response efficiency [34]. The STGAN method improves the quality of cloud-free images generated from satellite data by leveraging spatiotemporal correlations across multiple images, effectively reconstructing clear images from partially obscured data [49]. These advancements in satellite and edge computing underscore the transformative impact of innovative technologies on remote sensing capabilities, enhancing data processing efficiency and accuracy for better environmental monitoring and management. The integration of novel machine learning techniques allows for precise measurements of environmental variables, contributing to a comprehensive understanding of factors influencing eye health and ecological systems [5, 50, 16].

## 4 Impact of Lighting Environments on Eye Health

### 4.1 Environmental Uncertainty and Lighting

Environmental uncertainty complicates the assessment of lighting's effects on eye health due to variable weather conditions and limitations in current monitoring techniques. Unreliable weather forecasts impede accurate evaluations of environmental factors influencing ocular health [1]. For instance, light scattering in hazy conditions reduces contrast and visibility, obscuring critical details necessary for precise lighting assessments [50]. Atmospheric scattering, affected by lighting, distorts visual information in remote sensing data, complicating measurement accuracy [51]. This distortion is particularly problematic when evaluating artificial lighting's effects on circadian rhythms and visual comfort. Furthermore, interactions between Orbital Angular Momentum (OAM) beams and atmospheric turbulence provide real-time measurements of temperature and wind speed, essential for understanding environmental conditions affecting eye health [5].



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Current methods often fail to perceive and utilize spatial relationships between features at the same location over time, resulting in a loss of crucial spatial information [52]. This limitation hampers the ability to track and predict changes in lighting environments that could adversely affect ocular health. Stabilization mechanisms in systems like CANSAT enhance data accuracy, vital for reliable environmental monitoring [47]. The macular pigment (MP), associated with eye diseases such as age-related macular degeneration (AMD), underscores the necessity of accurately assessing lighting environments, as these conditions may exacerbate central field dysfunctions [17]. The Improved Adaptive Brovey method, effective in varying local image characteristics, highlights the need for adaptive techniques that address diverse environmental conditions affecting eye health assessments [43].

Addressing environmental uncertainty requires integrating advanced remote sensing technologies and innovative data processing methodologies. This integration enhances the precision and reliability of lighting impact assessments on eye health by leveraging advanced night light emission data for comprehensive analyses of light pollution and its implications for human well-being. Enhanced image fusion techniques, such as the Improved Adaptive Brovey method, refine spatial and spectral accuracy, facilitating a nuanced understanding of the relationship between artificial lighting and health outcomes [15, 20, 53, 43]. This approach is crucial for developing effective strategies to mitigate the adverse effects of environmental variability on ocular health.

#### **4.2 Technological Integration for Enhanced Monitoring**

Integrating advanced technologies is crucial for enhancing the monitoring of lighting environments, essential for evaluating their impacts on eye health. The development of compact, high-sensitivity spectrometers, such as the single-pixel p-graded-n junction spectrometer, represents a significant advancement. These spectrometers enable detailed spectral analysis, facilitating precise monitoring of lighting conditions and their potential effects on ocular health [54]. Innovations in multispectral imaging technologies, such as snapshot multispectral imaging, provide power-efficient solutions that operate independently of input polarization states, advantageous for continuous monitoring of lighting environments and offering comprehensive data necessary for understanding complex interactions between light and eye health [30].

In low-light conditions, enhancing image quality is critical for accurate environmental assessments. Techniques that effectively manage noise while improving low-light images, such as structure-based approaches, yield visually appealing and artifact-free results, ensuring accurate representation of lighting conditions and aiding evaluations of their impact on vision [55]. Furthermore, deploying wireless sensor nodes utilizing whispering gallery modes (WGM) allows for real-time monitoring and data collection. These sensors, equipped with wireless connectivity and user-friendly app interfaces, facilitate continuous assessment of lighting environments, providing valuable insights into their effects on eye health [56].

The integration of advanced remote sensing technologies, robust image enhancement models, and cutting-edge photonic sensors significantly improves the monitoring and analysis of lighting environments. This enables precise assessments of human activity, environmental impacts, and light pollution while addressing challenges such as noise reduction and spectral fidelity in low-light conditions [29, 15, 16, 55, 43]. By providing detailed and accurate data, these technologies support the development of strategies to mitigate the adverse effects of lighting on eye health, enhancing ocular health management and preventive care.

### **5 Applications in Diagnosing and Managing Ophthalmic Diseases**

The management of ophthalmic diseases is increasingly reliant on advanced technologies that have emerged in recent years. A notable advancement is ophthalmic imaging, which has significantly enhanced diagnostic precision through non-invasive techniques. This section examines the critical role of ophthalmic imaging in disease diagnosis and management, emphasizing innovative approaches and their clinical implications.

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## 5.1 Ophthalmic Imaging and Disease Diagnosis

Imaging technology advancements have transformed ophthalmic diagnostics, offering enhanced precision and non-invasive methods. The Self-Supervised Vision Transformer (SSVT) model achieves a diagnostic accuracy of 97.0

Hierarchical metric learning strategies have significantly improved classification accuracy in optical remote sensing scenes, achieving up to 85

Mobile health technologies, such as smartphone-based methods for observing spontaneous venous pulsations (SVPs), expand accessibility to diagnostic tools, showcasing the potential of everyday technology in enhancing ophthalmic care [57]. The 7-band CCD-in-CMOS Time Delay Integration (TDI) imager, known for high resolution and low power consumption, is adaptable for capturing multispectral data in ophthalmic imaging, providing crucial spectral information for precise diagnostics [40].

The fusion of artificial intelligence (AI) and telemedicine with imaging technologies is pivotal in improving ophthalmic disease diagnosis and management. Innovations like Visual Question Answering (VQA) systems enhance multimodal image interpretation, crucial for accurate diagnoses. Models such as EyeCLIP and VisionFM utilize extensive datasets and advanced learning strategies for enhanced disease classification and prognosis, while self-supervised methods like SSVT analyze unlabeled fundus images in resource-limited settings. These technologies streamline diagnostics and empower healthcare professionals to deliver timely and effective patient care in ophthalmology [13, 2, 14, 8]. These advancements not only improve diagnostic accuracy but also enhance patient outcomes through personalized treatment strategies.

## 5.2 Non-Invasive Diagnostic Methods

Remote sensing technology advancements have significantly improved non-invasive diagnostic methods in ophthalmology, offering new pathways for accurate disease detection. Hyperspectral imaging provides detailed spectral information essential for non-invasive diagnostics. The parallelization of the Recursive Hierarchical Segmentation (RHSEG) algorithm reduces processing time and energy consumption, enabling real-time applications and enhancing onboard processing capabilities [36].

In retinal imaging, advanced clustering algorithms, particularly Fuzzy C-Means (FCM), enhance the non-invasive evaluation of blood vessel conditions, crucial for early detection of ocular diseases like diabetic retinopathy and glaucoma. FCM improves segmentation accuracy in low-contrast retinal images, significantly boosting diagnostic sensitivity and specificity. Techniques such as EyeLearn and EyeCLIP optimize feature extraction from ophthalmic images, aiding in predicting visual field loss and disease classification [58, 59, 14]. These methods leverage hyperspectral imaging data to enhance diagnostic accuracy and patient outcomes.

Integrating remote sensing data with machine learning algorithms, as seen in DKCNet, addresses class imbalance in multi-label classification of ophthalmic diseases, improving diagnostic performance through advanced technologies like VQA and self-supervised learning [13, 60, 14, 8].

The coMPOD method for assessing macular pigment optical density (MPOD) offers a non-invasive approach to understanding macular health, with potential applications in early diagnosis of age-related macular degeneration (AMD). This method elucidates the relationship between MPOD and retinal eccentricity, revealing that circularly-oriented MPOD inversely correlates with retinal eccentricity within the 1.5° to 5.5° range. Given MP's association with central field dysfunctions and eye diseases, this insight underscores the potential for developing early diagnostic tests for various macular degenerative conditions [13, 17].

The incorporation of remote sensing technologies into non-invasive diagnostic methods marks a significant advancement in ophthalmic healthcare. These technologies enhance diagnostic accuracy and efficiency through multimodal imaging and artificial intelligence, providing critical insights into the influence of environmental factors on eye health. Innovative models like VQA and EyeCLIP enable healthcare professionals to better understand complex ocular conditions, ultimately leading to improved patient management strategies and outcomes. This development underscores the importance of interdisciplinary collaboration between medical experts and AI specialists to tackle existing challenges and optimize patient care for eye diseases [13, 14].

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### 5.3 Machine Learning and Image Analysis

Machine learning (ML) is integral to ophthalmic image analysis, significantly enhancing diagnostic accuracy and efficiency through advanced techniques like Visual Question Answering (VQA) and multi-modal foundation models such as EyeCLIP and VisionFM. These innovations leverage large datasets and integrate various imaging modalities to improve the interpretation of complex ophthalmic conditions, facilitating early detection and better patient outcomes. By combining computer vision with natural language processing, these models streamline diagnostics and address challenges like the scarcity of annotated data and the need for comprehensive evaluation methods, advancing ophthalmology [13, 2, 14]. The integration of ML techniques has led to the development of advanced algorithms capable of processing complex datasets, enhancing detection and classification of ophthalmic conditions.

A notable advancement is the application of self-supervised learning frameworks like SatMAE, which has demonstrated superior performance in both supervised and transfer learning tasks, bridging the performance gap between natural and satellite imagery and enabling more accurate feature extraction in ophthalmic image analysis [24]. This highlights the transformative impact of advanced ML models in the field.

In retinal imaging, ML algorithms automate segmentation and classification processes, critical for early detection of diseases such as diabetic retinopathy and age-related macular degeneration. Techniques like convolutional neural networks (CNNs) and attention-based models enhance image analysis accuracy, facilitating detection of subtle pathological changes. For instance, the EyeCLIP model leverages over 2.77 million multimodal ophthalmic images for improved disease classification and visual question answering, while SSVT achieves 97.0

Integrating ML with hyperspectral imaging (HSI) enhances the extraction of detailed spectral information, crucial for understanding ocular health. This approach addresses high dimensionality challenges and leverages modality-specific attributes to reveal unique insights into ocular conditions. Techniques like subspace learning for one-class classification allow for effective analysis of complex datasets, improving classification accuracy and facilitating precise assessments of ocular health through comprehensive spectral signature analysis [61, 25, 16]. This synergy enhances disease detection and monitoring, offering insights into underlying mechanisms of ophthalmic conditions.

The integration of machine learning into ophthalmic image analysis represents a transformative leap, significantly enhancing diagnostic accuracy and enabling tailored patient care. This advancement is exemplified by innovative approaches like VQA, which combines computer vision and natural language processing for improved interpretation of multimodal ophthalmic images. Models like EyeCLIP utilize extensive datasets for multi-modal analysis, while self-supervised techniques like SSVT demonstrate high-accuracy diagnosis potential even with unlabeled data. VisionFM's foundation model, trained on millions of diverse ophthalmic images, showcases superior performance in disease classification and prognosis, outperforming traditional methods and offering robust generalizability across imaging modalities. Collectively, these developments promise improved diagnostic capabilities and foster a more personalized, efficient approach to eye care, addressing the pressing need for effective solutions in managing ocular diseases [13, 14, 8, 9, 2]. As ML technologies continue to evolve, their integration into ophthalmic diagnostics is expected to yield further enhancements in the accuracy and efficiency of disease detection and management.

## 6 Environmental Monitoring and Eye Health

### 6.1 Remote Sensing and Environmental Factors

Remote sensing plays a crucial role in identifying environmental factors that influence eye health by offering extensive datasets and sophisticated analytical capabilities. High-resolution imaging techniques, such as those outlined in [62], facilitate detailed monitoring of natural phenomena, including water mapping, which is essential for understanding how changes in water bodies affect ocular health. However, accurately detecting temporal changes in remote sensing imagery is challenging due to noise and registration errors [63]. Addressing these issues is vital for ensuring the reliability of data used in assessing environmental impacts on eye health. Robust foundation models, bolstered by comprehensive datasets [38], significantly enhance the ability of remote sensing technologies to detect and analyze environmental changes.

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Applications such as SNOWWATCH demonstrate the use of remote sensing in environmental monitoring, utilizing user-generated content to identify factors affecting snow cover [18]. Monitoring snow cover is critical for understanding seasonal variations and their potential implications for eye health, especially in regions where snow influences light reflection and exposure. The integration of real-time data collection systems, as proposed in [1], enhances the identification of environmental factors impacting eye health by providing timely data, enabling proactive management of environmental risks associated with ocular conditions.

In disaster scenarios, rapid access to flood mapping data, as demonstrated by the approach in [34], improves response times and facilitates the assessment of environmental impacts on eye health. Additionally, the design of dual-band plasmonic absorbers, achieving high absorption rates in the NIR and MIR regions [4], contributes to a deeper understanding of environmental factors affecting eye health, enhancing the precision of remote sensing technologies in detecting subtle changes.

Remote sensing, particularly through the analysis of night light emissions and advanced multimodal datasets, provides critical insights into environmental factors like light pollution that significantly affect eye health and overall well-being. This technology enables the observation of human activities and environmental changes from space, facilitating urban mapping, monitoring light emissions, and understanding their health implications [15, 16]. Continuous advancements in remote sensing technologies are essential for improving our capacity to monitor and manage the environmental determinants of ocular health.

## 6.2 Applications of Environmental Data in Eye Health

The application of environmental data in eye health management is increasingly recognized as vital for understanding the complex interactions between environmental conditions and ocular health. Environmental IoT systems exemplify the potential of real-time data collection to enhance the understanding and management of complex environmental systems [3]. These systems enable continuous monitoring of variables such as air quality, light exposure, and weather conditions, crucial for assessing their impacts on eye health.

Integrating environmental data into ophthalmic health management allows for identifying risk factors associated with various eye conditions. Elevated ultraviolet (UV) radiation levels have been linked to cataracts and other ocular pathologies, underscoring the necessity for protective measures against UV exposure to maintain eye health and prevent degenerative conditions [17, 13, 11, 14, 12]. By leveraging environmental data, healthcare providers can develop targeted interventions to mitigate these risks, such as recommending protective eyewear or advising on safe outdoor exposure times.

Moreover, environmental data is critical for the early detection and management of seasonal eye conditions, such as allergic conjunctivitis, which can be exacerbated by pollen levels and air pollution. Real-time monitoring of environmental factors, facilitated by advanced IoT systems and innovative image analysis techniques, allows for immediate interventions that can significantly reduce the frequency and severity of symptoms in sensitive individuals, thereby enhancing public health outcomes [51, 18, 16, 1, 3].

In urban settings, the widespread use of artificial lighting poses risks to ocular health, including disruptions to circadian rhythms and increased eye strain. Environmental data collected through IoT systems can enhance urban lighting design by providing insights into light pollution and its health effects. This integration enables city planners to create lighting solutions that minimize adverse impacts on eye health, fostering a healthier visual environment. By leveraging advanced technologies like remote sensing and data analytics, cities can optimize lighting strategies to improve visibility while protecting inhabitants' health [51, 15, 50, 1, 3].

Furthermore, environmental data can support public health initiatives aimed at raising awareness of the relationship between environmental factors and eye health. By providing comprehensive information on how environmental conditions affect ocular health, individuals can make informed choices regarding lifestyle and protective measures, ultimately enhancing their ability to prevent and manage eye diseases such as glaucoma, age-related macular degeneration, and diabetic retinopathy. This knowledge is particularly important in light of advancements in ophthalmic treatments, including injectable hydrogels and multi-modal diagnostic technologies like EyeCLIP, which underscore the significance of early detection and personalized care in maintaining visual health [11, 14].

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The application of environmental data in eye health management represents a transformative approach to understanding and mitigating the impacts of environmental factors on ocular health. The ongoing development and integration of advanced environmental monitoring technologies are critical for formulating effective strategies to safeguard and improve eye health across various settings. Technologies such as machine learning-assisted optical sensing and AI-driven diagnostics enable precise measurements of environmental factors like temperature and wind speed, influencing ocular health. Additionally, innovative screening methods for conditions like diabetic retinopathy are evolving through teleophthalmology and automated detection systems, enhancing early diagnosis and treatment. The application of multi-modal imaging techniques in ophthalmology also paves the way for a more comprehensive understanding of eye diseases, further emphasizing the importance of integrating environmental data to address the multifaceted challenges of eye health [29, 15, 14, 5, 19].

## 7 Challenges and Future Directions

The integration of optical remote sensing in ophthalmic health monitoring presents both challenges and opportunities. Addressing the technological and methodological hurdles is crucial for advancing this field, as it involves significant computational demands and data processing complexities.

### 7.1 Technological and Methodological Challenges

Optical remote sensing technologies face several technological and methodological challenges in ophthalmic health monitoring. The high computational demands of hyperspectral analysis limit real-time applications, especially with high-resolution images from modern sensors [36]. Identifying modality-specific features within multimodal datasets is crucial for successful integration [16]. The creation of extensive labeled datasets in satellite imagery is labor-intensive and poses a barrier to effective analysis [44]. Current denoising methods often require human intervention for parameter tuning, impractical for large-scale applications [64]. Cloud removal benchmarks usually lack comprehensive multispectral information, limiting their utility in dynamic environments [65]. Monitoring dynamic environments is further complicated by methods that require long integration times and do not measure key turbulence parameters directly [5]. Retinal image segmentation is hindered by noisy backgrounds and vessel width variability, affecting diagnostic accuracy. Class imbalances in datasets like ODIR-5K complicate robust diagnostic algorithm development, leading to biased model training and reduced classification accuracy for minority classes [9]. Addressing these challenges is essential for advancing the integration of remote sensing in ophthalmic health monitoring, improving spatial resolution, multispectral capabilities, and automated detection systems for timely diagnosis and intervention in conditions like diabetic retinopathy [57, 20, 15, 16, 19].

### 7.2 Data and Communication Challenges

Integrating optical remote sensing into ophthalmic health monitoring introduces data and communication challenges. Handling large volumes of high-resolution data requires robust computational resources and efficient management strategies. Distributed deblurring of large images necessitates advanced algorithms to maintain data integrity [66]. Evaluating remote sensing models involves cross-validation techniques to assess performance metrics like Mean Squared Error and uncertainty intervals, crucial for data reliability [39, 16]. Communication challenges arise in deploying remote sensing technologies in remote or resource-limited areas with inadequate infrastructure. Transmitting large datasets over limited bandwidth can result in delays and data loss, undermining environmental monitoring efforts. Innovative solutions like integrated photonics, satellite edge computing, and advanced remote sensing technologies are essential for improving data transmission capabilities [29, 15, 38, 45, 3]. Integrating diverse data sources such as satellite imagery, IoT-based sensors, and ophthalmic records requires advanced data fusion techniques capable of harmonizing information from various modalities. Utilizing algorithms like the Brovey and contourlet methods can enhance spatial resolution while preserving spectral information, improving monitoring of natural phenomena and health conditions [67, 62, 16, 31, 43]. Developing standardized protocols and communication frameworks is essential for facilitating interoperability and data sharing across platforms. Addressing data and communication challenges in remote sensing is critical for advancing these technologies in ophthalmic health monitoring, enhancing data management and communication strategies through

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IoT systems and multimodal learning techniques to improve precision and efficiency of environmental assessments [13, 68, 1, 3].

### 7.3 Integration and Application Challenges

The integration and application of optical remote sensing in ophthalmic contexts face challenges due to the complexity of environmental and health data. Effective integration of multimodal data sources requires advanced data fusion techniques to harmonize datasets like satellite imagery, IoT sensor data, and clinical ophthalmic records. This integration is critical for understanding environmental factors affecting eye health but is hindered by a lack of standardized protocols and interoperability issues [3]. Data quality and resolution variability in remote sensing imagery, influenced by atmospheric conditions like cloud cover and haze, can obscure critical details necessary for accurate assessments, necessitating robust image processing and enhancement techniques [50]. Real-time data processing capabilities further complicate timely decision-making in health management [1]. Adapting remote sensing technologies to the specific requirements of ophthalmic applications, which often demand high precision and sensitivity, poses another challenge. Developing specialized algorithms and models tailored to ophthalmic diagnostics requires substantial computational resources and expertise that may not be available in all healthcare settings [9]. Logistical challenges in deploying these technologies in resource-limited settings, including infrastructure availability and trained personnel, must also be addressed. Strategic investments in capacity building and partnerships between technology developers and healthcare providers are necessary to overcome these obstacles [47]. Enhancing the application of optical remote sensing technologies in ophthalmic health monitoring requires addressing integration and implementation challenges, developing advanced sensors with high spatial resolution and multispectral imaging capabilities to capture and analyze spectral characteristics of light emissions relevant to human health [15, 16].

### 7.4 Future Research Directions

Future research in integrating optical remote sensing with ophthalmic health monitoring should prioritize developing higher spatial resolution and multispectral sensors to improve remote sensing capabilities and provide detailed environmental data [40]. Optimizing sensors for low-light conditions and exploring additional spectral bands could enhance imaging capabilities. In hyperspectral imaging, research could focus on optimizing the Recursive Hierarchical Segmentation method for various hardware configurations and investigating alternative dissimilarity measures to extend applicability to mixed-pixel classification problems [36]. Refining filtering techniques used in Spectral Extraction of Distinctive Latent Variables across multimodal datasets could yield valuable insights into ophthalmic diseases [16]. Integrating machine learning methodologies like SatMAE should continue to be optimized for efficiency, focusing on better positional encodings and spectral band groupings [24]. Future research could explore incorporating the asymmetric Laplacian distribution into diffusion models to improve adaptability to noise types, enhancing image analysis robustness [64]. Enhancing object detection frameworks like CenterFPANet for improved generalization capabilities and performance in challenging categories should be a focus [35]. Improving cloud removal techniques through additional features or semantic information could enhance diffusion models, improving remote sensing imagery quality [65]. Exploring refinements in the SOCM-3 model architecture and expanding datasets could bolster the robustness and applicability of satellite imaging technologies [38]. Future research should encompass innovative approaches such as Visual Question Answering in ophthalmology, combining computer vision and natural language processing to enhance interpretation of multimodal ophthalmic images, improving diagnostic accuracy while addressing challenges like annotated dataset scarcity. Exploring new screening technologies for diabetic retinopathy, including artificial intelligence and teleophthalmology, promises to optimize screening strategies and extend applications beyond vision preservation to encompass cardiovascular and cognitive health monitoring. Advancements in remote sensing of night lights could further improve environmental monitoring and understanding of light pollution's health effects. These efforts are expected to drive significant innovations in environmental monitoring and ophthalmic health management [15, 13, 19]. By focusing on these key areas, we can enhance the precision, efficiency, and applicability of remote sensing technologies, contributing to improved health outcomes and effective environmental management.

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## 8 Conclusion

The convergence of optical remote sensing technologies with ophthalmic health and environmental monitoring represents a pivotal advancement, offering substantial benefits for early disease detection and comprehensive environmental evaluations. Through the use of cutting-edge imaging techniques, spectrometry, and AI-driven methodologies, these technologies enhance the precision of remote sensing data, thereby expanding our comprehension of the environmental determinants of eye health. The advancements in multispectral and hyperspectral imaging, coupled with innovations in satellite and edge computing, exemplify the transformative impact of these technologies in elevating remote sensing capabilities.

This survey highlights the critical influence of lighting environments on ocular health, emphasizing the importance of precise environmental monitoring to prevent potential adverse effects. The integration of remote sensing technologies has substantially advanced the diagnosis and management of ophthalmic diseases through non-invasive techniques and machine learning-enhanced image analysis, resulting in improved diagnostic precision and better patient outcomes.

Despite these advancements, several challenges remain, particularly in data management, communication protocols, and the integration of heterogeneous data sources. Future research must focus on overcoming these obstacles by developing higher-resolution sensors, refining machine learning algorithms for remote sensing applications, and enhancing the robustness of image processing methodologies.

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