CatScreen: A Large MultiModal Benchmark Dataset for Cataract Screening

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Abstract

Low-cost slit-lamp imaging holds significant potential for transforming eye care by facilitating affordable and scalable cataract diagnosis. However, the development of robust, generalizable AI-based cataract screening solutions is currently constrained by the limited availability of large-scale, richly annotated datasets. To address this critical gap, we introduce CatScreen, a comprehensive multimodal benchmark dataset specifically designed for cataract screening, comprising approximately 18,000 slit-lamp images collected from 2,251 subjects using a portable slit-lamp camera. CatScreen is structured into three subsets: (i) a clean set meticulously annotated by ophthalmology experts across clinically relevant dimensions, including image gradability, quality assessment, illumination type, diagnostic classification, cataract subtype, and severity grading according to established standards; (ii) a noisy-labeled set that simulates real-world annotation inaccuracies; and (iii) an unlabeled set intended to foster the development of self-supervised and semi-supervised learning approaches. Furthermore, CatScreen integrates extensive subject-level metadata encompassing demographics, lifestyle factors, and detailed clinical histories, providing a holistic perspective for comprehensive analysis. To enhance model interpretability and clinical applicability, a subset of images has been precisely annotated to delineate anatomical structures in both healthy and pathological states. Additionally, this work presents two complementary AI frameworks, Structured Sequential Analysis and Multitask Learning, each offering distinct yet synergistic approaches toward enhancing model interpretability and efficiency. CatScreen thus provides researchers with a robust foundation to advance reliable, interpretable, and generalizable cataract screening solutions, significantly improving access to quality eye care diagnostics, particularly in underserved and resource-limited regions.

1 Introduction

Cataract is characterized by clouding of the eye's natural lens, resulting in diminished visual acuity. If left untreated, cataracts can progress to complete blindness or significantly impair an individual's mental well-being Wang et al. (2024). Figure 1 illustrates representative examples of cataractous lens compared to healthy eyes and natural crystalline lens affected by other ocular conditions. Globally, cataract remains the predominant cause of blindness, impacting approximately 15.2 million individuals, constituting about 45% of global blindness cases (Steinmetz et al., 2021; of the Global Burden of Disease Study et al., 2024). Although cataracts have traditionally been prevalent among elderly populations, recent epidemiological studies report a worrying rise in prevalence among younger age groups. This demographic shift is associated with multiple modifiable and non-modifiable risk factors, including smoking, radiation exposure, and an increasing incidence of diabetes (Thompson & Lakhani, 2015). Timely detection and early surgical intervention through lens replacement remain the definitive treatment options, thereby emphasizing the necessity of effective and accessible screening methods.

Conventionally, cataract diagnosis relies heavily on manual examinations performed by trained ophthalmologists using slit-lamp microscopy. This clinical evaluation requires significant expertise and extensive practical experience to accurately detect cataracts, classify their subtypes, and grade their severity. Despite its effectiveness, this traditional diagnostic approach faces substantial limitations, particularly in resource-limited

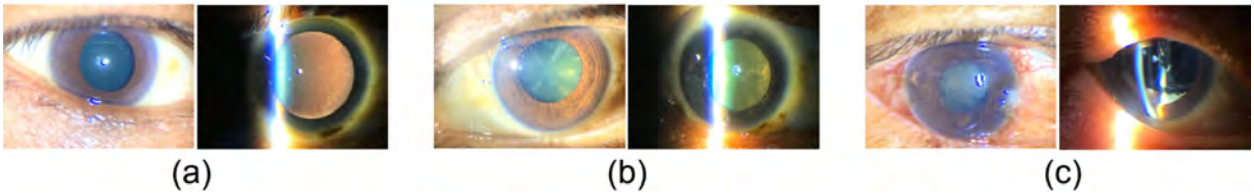


Figure 1: Sample images of eyes for (a) normal, (b) cataract condition characterized by lens clouding, and (c) various other eye conditions affecting different ocular structures.

settings characterized by insufficient qualified healthcare personnel (Flaxman et al., 2017). Consequently, a significant fraction of the global population, especially those in underdeveloped and underserved regions, lacks access to timely diagnosis and effective treatment options. This disparity underscores the urgent need for innovative, scalable, and accessible diagnostic solutions that can bridge existing healthcare gaps and enhance ocular health outcomes for diverse populations.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) present promising avenues to address these diagnostic challenges. AI techniques have shown substantial potential in medical imaging analysis, particularly in detecting, segmenting, classifying, and grading various ocular diseases (Gour et al., 2023). Integrating AI-driven automated systems into cataract screening workflows can significantly enhance diagnostic accuracy, efficiency, and accessibility, offering profound benefits to remote and resource-constrained environments. However, the development and successful deployment of robust AI-based diagnostic tools fundamentally depend on the availability and quality of comprehensive, diverse, and meticulously annotated datasets.

Several research initiatives have leveraged slit-lamp imaging datasets to automate cataract detection and classification. However, current slit-lamp datasets often suffer from limitations related to data diversity, completeness, and annotation depth, hindering their applicability to generalizable and robust diagnostic systems. For instance, Foong et al. (2007) and Shimizu et al. (2023) focused primarily on nuclear cataracts, while Wang et al. (2023) concentrated exclusively on cortical cataracts. Such narrowly focused datasets inherently lack comprehensive diversity, thus limiting their generalizability. Similarly, datasets provided by Jiang et al. (2021) and (Son et al., 2022), although extensive, primarily offer limited annotation dimensions, restricting the clinical relevance and interpretability of AI solutions derived from them. Notably absent from these datasets are critical parameters such as detailed assessments of image quality, precise classification of cataract subtypes, and standardized grading of cataract severity—all of which are essential elements in comprehensive ophthalmic diagnosis. Consequently, existing AI-based methods developed from such datasets encounter significant biases and constraints in real-world diagnostic scenarios.

Table 1: Existing slit-lamp image-based datasets for cataract diagnosis and their respective characteristics

Author	Device Used	No. of Subjects	No. of Images	Metadata	Image Quality?	Disease Grading?	Remarks
Foong et al. (2007)	Topcon DC-1 digital slit-lamp	1000	1000	✓	✗	✓	Nuclear Cataract
Jiang et al. (2021)	slit-lamp	536	886	✗	✗	✓	Infantile Cataract
Jiang et al. (2021)	slit-lamp	433	757	✗	✗	✓	Infantile Cataract
Son et al. (2022)	SL-D7[TMS, Inc] D850 [Nikon, Inc]	596	1972	✓	✗	✓	Cataract detection and grading
Wang et al. (2023)	slit-lamp	2150	2150	✗	✗	✓	Cortical cataract
Shimizu et al. (2023)	Smart Eye Camera	1812	38320 frames	✗	✗	✗	Nuclear cataract
Proposed CatScreen	Remidio Portable Slit Lamp PSL-D20	2251	18640	✓	✓	✓	Cataract detection, grading, quality analysis, multimodal data

To systematically address these limitations and foster the development of robust and clinically relevant AI-based cataract screening tools, we introduce CatScreen, an extensive, multimodal, and comprehensively annotated dataset acquired through an affordable, portable slit-lamp imaging device. CatScreen comprises over 18,000 slit-lamp images collected from approximately 2,251 diverse subjects. Each image is thoroughly annotated across several clinically relevant dimensions, including diagnostic classification, image gradability, quality assessments, cataract subtype identification, and severity grading, all adhering to established ophthalmological standards. Additionally, comprehensive subject-level metadata capturing essential demographic variables, lifestyle factors, and clinical histories accompanies the dataset. To enhance AI model explainability and clinical relevance, a subset of images includes detailed segmentation annotations of critical anatomical structures, such as the lens, cornea, iris, and pathological regions.

By providing a richly annotated and multidimensional ocular dataset, CatScreen uniquely addresses critical shortcomings of existing datasets and sets a foundational resource for developing advanced, explainable, and clinically robust AI diagnostic tools. The depth and diversity of annotations ensure that AI methods developed using CatScreen will be applicable and generalizable across various clinical settings, enhancing their utility in real-world ophthalmic diagnostics. Given these comprehensive features, CatScreen directly addresses the following critical clinical and technical research questions:

Q1: How can slit-lamp image quality be reliably and objectively evaluated?

Q2: How can the type of illumination employed in slit-lamp imaging be accurately identified, and its impact on diagnostic outcomes quantified?

Q3: How can slit-lamp images be effectively categorized into normal, cataractous, or other ocular conditions?

Q4: How can specific cataract subtypes be accurately identified and differentiated?

Q5: Upon diagnosing cataract presence, how can cataract severity be consistently and objectively assessed?

The structured and comprehensive nature of CatScreen ideally positions it for diverse screening and diagnostic modeling frameworks, including structured sequential analyses and multitask learning methodologies, as elaborated in the subsequent problem formulation section.

2 Problem Formulation

The problem addressed in this work is the automated screening and diagnostic assessment of cataracts, aiming to replicate the detailed multi-stage clinical evaluation typically performed by ophthalmologists. Specifically, this assessment involves evaluating the quality of slit-lamp images, classifying illumination conditions, diagnosing the presence or absence of cataracts, identifying specific cataract subtypes, and grading cataract severity. The structured assessment utilizes slit-lamp images paired with comprehensive patient metadata to provide clinically informed predictions.

Formally, we denote an input slit-lamp image as $I \in \mathbb{R}^{H \times W \times C}$, where H, W, and C correspond to image height, width, and color channels, respectively. Additionally, patient metadata is represented by a feature vector $M \in \mathbb{R}^d$, containing demographic details, lifestyle factors, and clinical histories, such as age, gender, diabetic status, and ocular medical records. The task objective is to predict a set of clinically relevant diagnostic attributes, denoted as $A = (Q, T, D, C, G)$, where each attribute represents:

- $Q \in \text{Good}, \text{Acceptable}, \text{Poor}$: Image quality assessment.
- $T \in \text{Diffuse}, \text{Direct Focal}, \text{Retro}$: Illumination type classification.
- $D \in \text{Normal}, \text{Cataract}, \text{Others}$: Diagnostic categorization.
- $C \in \text{No cataract}, \text{Nuclear}, \text{Cortical}, \text{PSC}, \text{Pseudophakia}, \text{Others}$: Cataract subtype identification.
- $G \in \text{Not Applicable}, \text{Mild}, \text{Severe}$: Severity grading of cataract.

This diagnostic formulation can be approached via two distinct yet complementary methodologies: (1) structured sequential analysis, mirroring the sequential decision-making workflow of clinical practitioners, or (2) multitask learning, where all diagnostic attributes are concurrently predicted from shared inputs.

To explicitly represent causal relationships and enhance interpretability, we adopt Structural Causal Models (SCMs) for the sequential analysis, formally defined as follows:

$$Q = f_Q(I, \epsilon_Q), \tag{1}$$
$$T = f_T(I, Q, \epsilon_T), \tag{2}$$
$$D = f_D(I, M, Q, T, \epsilon_D), \tag{3}$$
$$C = f_C(I, M, D, \epsilon_C), \tag{4}$$
$$G = f_G(I, M, D, C, \epsilon_G), \tag{5}$$

where $\epsilon_Q, \epsilon_T, \epsilon_D, \epsilon_C, \epsilon_G$ denote exogenous noise variables, thus clearly delineating causal pathways and enhancing transparency in the diagnostic workflow.

Alternatively, the multitask learning formulation employs a unified predictive model f_θ parameterized by model weights θ, simultaneously predicting all attributes:

$$(\hat{Q}, \hat{T}, \hat{D}, \hat{C}, \hat{G}) = f_\theta(I, M). \tag{6}$$

This model is optimized by minimizing a weighted sum of task-specific classification losses:

$$\mathcal{L}(\theta) = \lambda_Q \mathcal{L}_Q + \lambda_T \mathcal{L}_T + \lambda_D \mathcal{L}_D + \lambda_C \mathcal{L}_C + \lambda_G \mathcal{L}_G, \tag{7}$$

with each individual loss $\mathcal{L}_.$ defined by categorical cross-entropy:

$$\mathcal{L}(y, \hat{y}) = -\sum_{j=1}^{K} y_j \log(\hat{y}_j), \tag{8}$$

where y is the one-hot encoded ground-truth vector, and $\hat{y}$ is the predicted probability distribution over K classes.

Acknowledging the advantages inherent in each modeling approach, we explicitly structured our CatScreen dataset to facilitate both methodologies. This flexibility ensures the development of robust, versatile, and clinically meaningful automated cataract screening systems.

3 CatScreen Dataset

The CatScreen dataset is a meticulously curated resource, comprising over 18,000 slit-lamp images acquired using low-cost, portable handheld slit-lamp cameras. Aiming to deliver a comprehensive and affordable solution for cataract diagnosis, this dataset addresses critical gaps identified in existing ophthalmic image repositories. Prioritizing patient privacy and adhering strictly to ethical guidelines, all Protected Health Information (PHI), including names, guardian details, contact numbers, email addresses, and other sensitive data, has been carefully anonymized and removed. To maintain data integrity without compromising confidentiality, each image is assigned a unique, non-identifying identifier indicating patient ID, pupil dilation state (dilated or undilated), eye side (right or left), and capturing device details. Preliminary preparations, including rigorous site selection, commenced in August 2022, leading to an extensive data collection phase spanning from December 2022 through January 2024. This section elaborates on the detailed prerequisites, device specifications, data acquisition procedures, and the exhaustive annotation methodologies utilized.

3.1 Pre-requisites and Device Specifications

This subsection describes the essential preparatory steps, patient recruitment protocols, exclusion criteria, and technical specifications of the imaging device employed.

1. **Ethical Considerations**: Prior to data collection, formal approvals were obtained from the Institutional Ethics Committees of the Postgraduate Institute of Medical Education and Research (PGIMER) (approval number PGI/IEC-11/2022-2633) and Sri Sankaradeva Nethralaya (SSN/IEC/AUGUST/2022/01). Adherence to the ethical standards outlined in the Declaration of Helsinki was strictly maintained throughout the study. Participants were given detailed briefings on the study's objectives, methodologies, and potential implications. Written informed consent was obtained from all participants, and dedicated sessions were held to address and resolve the questions of the participants.

2. **Exclusion Criteria**: To guarantee data consistency, individuals with active ocular infections or diagnosed type 1 diabetes mellitus were excluded from participation. These criteria ensured the collection of relevant and high-quality data suitable for developing reliable diagnostic models.

3. **Device Specifications**: The imaging data was captured using the Remidio Portable Slit Lamp PSL-D20 (Remidio Innovative Solutions Pvt. Ltd., Bangalore, India), a handheld, versatile, and portable digital slit-lamp camera. Designed explicitly for efficient mobile eye examinations, the PSL-D20 device offers adjustable slit widths ranging from 1 to 12mm and slit angles adjustable within ± 45 degrees, supporting both diffuse and direct focal illumination. The device seamlessly integrates with an Apple iPhone SE camera, leveraging its high-resolution imaging capabilities. It supports multiple specialized imaging modes, including standard color imaging, green (red-free), and blue illumination. Equipped with magnification options of $10\times$ and $16\times$, and a working distance of 61mm, the PSL-D20 ensures high-quality imaging under diverse clinical settings. Images are captured at a high resolution of 3024×4032 pixels, while videos are recorded at 1920×1080 pixels, further enhancing data clarity and clinical applicability.

3.2 Data Collection

The CatScreen dataset comprises 18,640 slit-lamp images from 2,251 diverse participants collected across multiple clinical sites. In addition to visual imagery, CatScreen includes comprehensive metadata capturing detailed socio-demographic and clinical characteristics of each participant, significantly enriching the dataset's analytical potential. To facilitate various research approaches, CatScreen is systematically categorized into three distinct subsets:

- **Clean Set**: Featuring 9,915 meticulously annotated images from 1,271 participants, this subset serves as the foundation for robust, supervised learning model training. Domain experts provided exhaustive annotations covering essential parameters including image gradability, diagnostic categorization, cataract subtype identification, severity grading, and illumination type. The detailed distribution of annotations across patients and attributes is presented in Table 2a.

- **Noisy Set**: Consisting of 3,267 images from 505 participants, this subset includes annotations with varying degrees of accuracy to emulate realistic clinical environments, where annotations may inherently contain errors. Such a dataset aids in the development and evaluation of models resilient to annotation noise.

- **Unlabelled Set**: Containing 5,481 images without diagnostic annotations, this subset facilitates the exploration of innovative approaches such as self-supervised, semi-supervised, and active learning methodologies, allowing effective utilization of unlabeled data to augment model robustness and generalizability.

3.2.1 Image Collection Protocol

Images were systematically captured following the protocols recommended by the WHO simplified grading system. These images were collected under both dilated and undilated pupil conditions, using the following specialized imaging techniques:

- **Direct Optical Section Images**: Captured at 10× magnification, with a slit width of 0.2 mm and a slit-beam orientation of 30 degrees, enabling detailed visualization of distinct lens layers.
- **Direct Diffuse Illumination Images**: Obtained at 5× magnification, with the illuminating arm positioned at a 45-degree angle relative to the microscope. This approach provides comprehensive visualizations of the anterior segment of the eye in both dilated and undilated states.
- **Indirect Retro-Illumination Images**: Acquired under strictly controlled, dimly lit conditions (below 15 lux) with a slit lamp-mounted iPhone SE camera flash, exclusively in dilated conditions, offering enhanced visualization of posterior lens structures and subtle abnormalities.

3.2.2 Comprehensive Metadata

To maximize the clinical and research value of the CatScreen dataset, an extensive array of patient metadata was collected, encompassing a broad spectrum of factors potentially influencing cataract development and progression. Summarized comprehensively in Table 2b, key metadata elements include:

- **Demographic Data**: Participant ages ranged from 35 to 92 years, averaging approximately 57 years, with a well-balanced gender distribution comprising 45% females and 54% males.
- **Health Conditions**: Clinical histories documenting the presence of diabetes, hypertension, and other systemic conditions that could influence ocular health.
- **Eye Health History**: Detailed ocular health records capturing previous incidents of eye inflammation, myopia, ocular surgeries, eye trauma, and topical ocular disorders.

Through its meticulous curation, rigorous annotations, and extensive metadata, CatScreen stands as a unique and invaluable resource, poised to significantly advance AI-driven cataract screening technologies, enabling their widespread clinical adoption and deployment, particularly in underserved and resource-limited regions.

4 Data Annotation

Ensuring accuracy and consistency in dataset annotation is pivotal for developing robust and clinically reliable diagnostic models. To achieve this objective, the CatScreen dataset employed a meticulous three-tiered annotation process, structured to maximize precision, minimize annotation biases, and maintain high-quality standards throughout.

4.1 Three-tiered Annotation Structure

The annotation procedure was designed to leverage progressively specialized expertise at each annotation level:

1. **Level 1 – Initial Annotation**: Two experienced optometrists, each holding a bachelor's degree in optometry with a minimum of three years of hands-on experience in retinal and anterior segment imaging, performed initial annotations. These annotations provided a foundational layer for subsequent refinement.
2. **Level 2 – Secondary Review and Refinement**: A senior optometrist possessing a master's degree in optometry and over five years of clinical and imaging experience conducted an exhaustive secondary review. This intermediate stage involved meticulous refinement and correction of initial annotations to resolve ambiguities and discrepancies.

Label	Classes	Train	Val	Test	Total Images
Diagnosis	Normal	1845	251	545	**2641**
	Cataract	3627	523	996	**5146**
	Others	1526	224	378	**2128**
Cataract Type	Normal	1845	251	545	**2641**
	Nuclear Cataract	3357	479	924	**4760**
	Cortical Cataract	184	30	48	**262**
	Posterior SC	75	14	24	**113**
	Pseudophakia	1495	220	365	**2080**
	Others	42	4	13	**59**
Cataract Grade	Not Applicable	3371	475	923	**4769**
	Mild	2970	428	796	**4194**
	Severe	657	200	95	**952**
Image Quality	Good	134	22	20	**176**
	Acceptable	6112	871	1680	**8663**
	Bad	752	105	219	**1076**
Illumination type	Diffuse Illumination	2130	296	606	**3032**
	Direct Focal	2996	423	795	**4214**
	Retro	1872	279	518	**2669**

(a)

Set			**Gender**			**Age**		
	Participants			Clean	Noisy		Clean	Noisy
Clean Set	1271		Females	578	231	Max	92	86
Noisy Set	505		Males	693	274	Min	35	51
						Mean ± Std	57.2 ± 9.96	61 ± 7.22
Diabetes Status			**Hypertension Status**			**Systemic Illness Status**		
	Clean	Noisy		Clean	Noisy		Clean	Noisy
No	815	199	No	710	181	No	1002	295
Yes	456	306	Yes	561	324	Yes	269	210
Eye Problem Status			**Use of Spectacles**			**Ocular Surgery Done?**		
	Clean	Noisy		Clean	Noisy		Clean	Noisy
No	396	195	No	367	166	No	667	354
Yes	875	310	Yes	904	339	Yes	604	151

(b)

Table 2: Showcasing the (a) distribution of each label in training, validation and testing, and (b) summarizing the distribution of participants of clean and noisy sets based on sociodemographic factors and other clinical characteristics.

3. **Level 3 – Expert Validation**: Final validation and oversight were provided by a retina-trained ophthalmologist with over a decade of clinical and diagnostic experience. This expert-level validation ensured maximum accuracy, consistency, and clinical relevance of the final annotations, thereby enhancing the dataset's reliability and applicability in developing diagnostic AI solutions.

The annotation process was systematically divided into three essential phases: gradability assessment, ground-truth collection, and anatomical and pathological annotation.

4.2 Gradability Assessment

Image gradability is crucial for ensuring diagnostic accuracy in ophthalmic imaging research. Recognizing its importance, a rigorous two-stage gradability assessment protocol was developed and implemented.

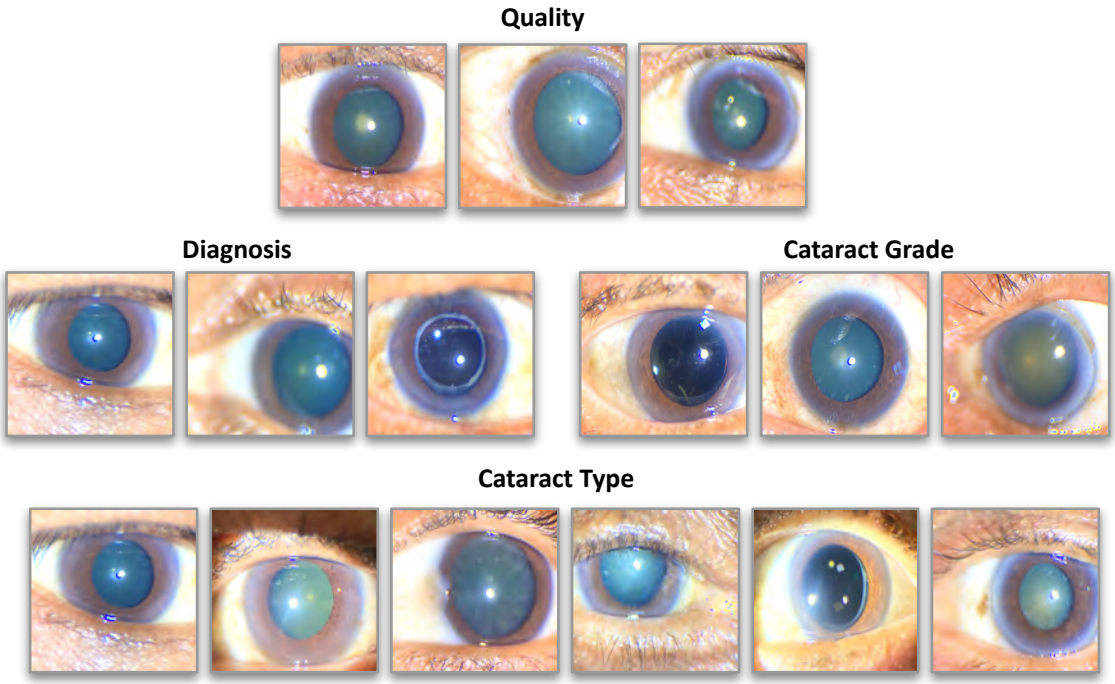


Figure 2: Presents the samples of the CatScreen in diffuse illumination setting across various labels.

In the first stage, trained opticians assessed the image quality in real-time at the point of capture. Images failing predefined stringent criteria related to clarity, sharpness, and contrast were immediately discarded and replaced with newly captured images. The second stage involved Level 1 annotators performing a comprehensive reevaluation of the images using identical quality standards. Only those images passing both stages of rigorous scrutiny were deemed gradable and included for detailed annotation and further analysis.

The key parameters evaluated during this gradability assessment included:

- Clear visibility of at least 80% of the anterior segment of the eye.
- Distinct visibility of critical morphological features including the iris, lens, cornea, and other anterior ocular structures.
- Optimal sharpness and contrast for accurate clinical interpretation.
- At least 95% clarity of all morphological landmarks.

4.3 Ground-truth Collection

Each selected image underwent a detailed multi-label annotation process, capturing comprehensive diagnostic insights. Figure 2 showcases the multi-label annotation of some sample images in diffuse illumination.

a. Image Quality: Annotated using a 10-point Likert scale, the image quality ratings were aggregated into three distinct categories to mitigate subjective variability: Poor (Grades 1–3), Acceptable (Grades 4–8), and Good (Grades 9–10).

b. Illumination Type: Images were categorized based on three illumination techniques commonly used in slit-lamp imaging:

- **Direct Focal Illumination**: Utilizing a narrow, focused beam directed to highlight specific anterior ocular structures such as the lens and cornea, enhancing visibility of fine details and layer structures.

- **Diffuse Illumination**: Employing a broad, uniform light source, this method provides an overall visualization of the anterior segment, suitable for general screening and holistic assessment.
- **Retro-Illumination**: Involving light reflected from behind the retina to visualize the posterior lens, this method accentuates subtle abnormalities such as posterior lens opacities.

c. Diagnostic Label: Images were classified into three diagnostic categories:

- **Normal (No)**: Images with no detectable abnormalities.
- **Cataract (Cat)**: Images exhibiting any evidence of lens clouding.
- **Others (Oth)**: Images indicating conditions such as pseudophakia, pterygium, conjunctivitis, or corneal scarring.

d. Cataract Type: Six categories were utilized for identifying cataract subtypes:

- **No Cataract**: No visible opacification.
- **Nuclear Cataract**: Opacities predominantly within the lens nucleus.
- **Cortical Cataract**: Peripheral lens opacities characterized by wedge-like patterns.
- **Posterior Subcapsular Cataract (PSC)**: Opacities located posteriorly, affecting the lens capsule's back.
- **Pseudophakia (PP)**: Presence of an artificial intraocular lens.
- **Others**: Any conditions not fitting exclusively into above categories or combinations thereof.

e. Cataract Grade: Cataract severity was classified into three distinct grades:

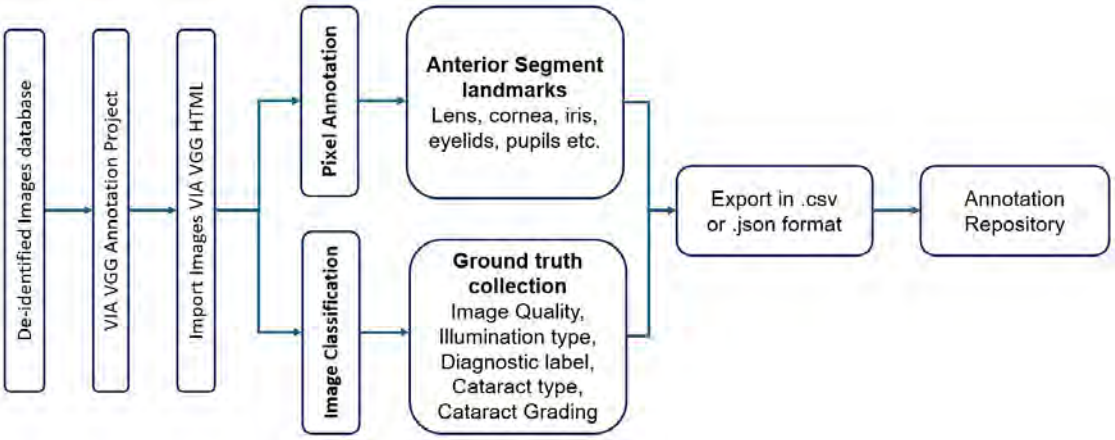
- **Not Applicable**: For normal or other non-cataract cases.
- **Mild**: Early-stage cataracts with minimal to moderate lens opacity.
- **Severe**: Advanced cataracts characterized by dense and extensive lens opacification.

4.4 Anatomical and Pathological Annotations

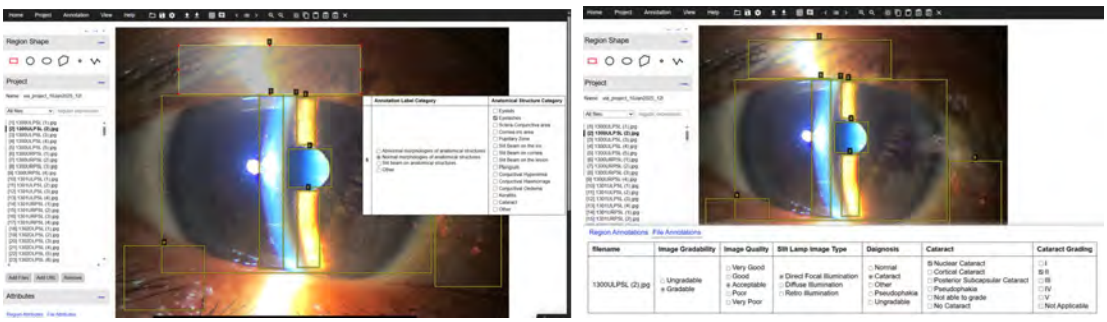
To further enhance the dataset's interpretability and clinical relevance, a subset of images underwent meticulous segmentation-based annotations. Using the Oxford VGG Image Annotator tool (available at [`https://www.robots.ox.ac.uk/~vgg/software/via/via_demo.html`]), annotators delineated key ocular structures such as the cornea, iris, lens, and sclera. Additionally, pathological features such as cataracts, corneal scars, pterygium, conjunctival hemorrhages, and edema were accurately identified and annotated. These detailed annotations are critical for training AI models capable of anatomically accurate diagnostic predictions and for validating the clinical interpretability of the models. Sample annotated images are presented in Figure 3, and precise coordinates of each annotation are systematically documented.

4.5 Quality Assurance Protocol

A comprehensive quality assurance (QA) protocol was implemented, involving initial annotations by Level 1 annotators followed by systematic reviews by Level 2 annotators. For initial QA validation, the first 500 annotated images underwent inter-annotator agreement analysis, specifically targeting diagnostic labels. A kappa score threshold of 0.60 was set as the standard for acceptable agreement. Any discrepancies or disagreements were rigorously addressed in structured group discussions involving the expert Level 3 annotator. Following this initial validation phase, continuous monthly QA checks were conducted, reviewing 25% of annotated images over three consecutive months. This rigorous annotation and QA protocol ensured high levels of annotation precision and consistency, reinforcing CatScreen's suitability as a reliable and clinically valuable dataset for developing advanced ophthalmic diagnostic AI solutions.



(a)



(b)

Figure 3: Presents (a) the annotation process where the input image is classified corresponding to multiple labels and (b) various annotations for anatomical and pathological regions in a slit-lamp image.

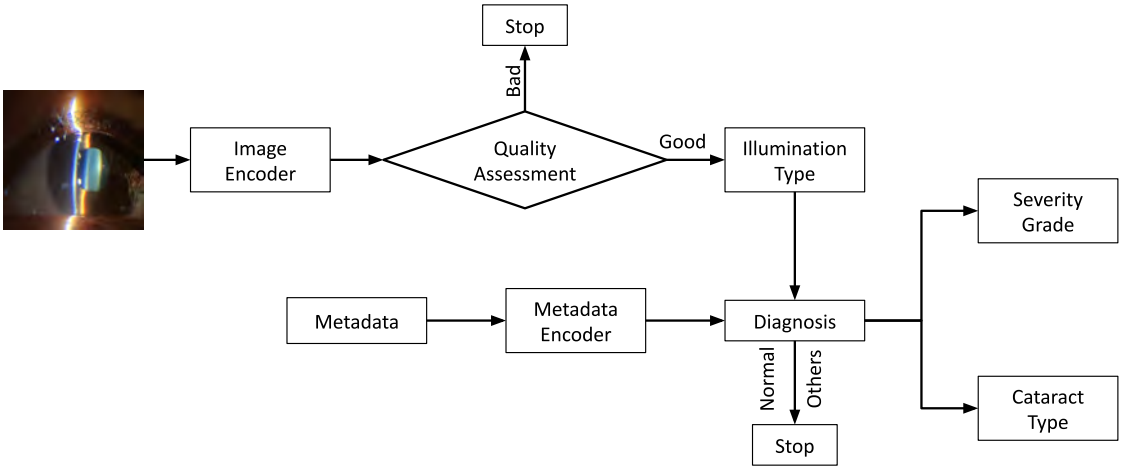
4.6 Data Records

The Catscreen dataset will be made publicly available for research purposes upon acceptance. A sample snapshot of the dataset is available at https://github.com/Anonymousresearcher002/Data2025.git. There is a primary folder named CatScreen with the following directory structure:

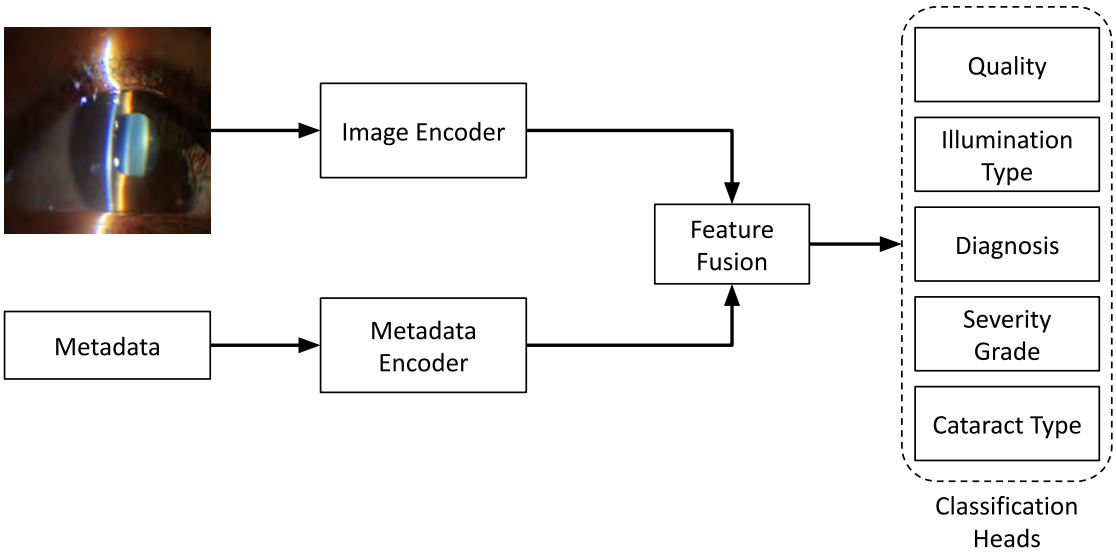
- Clean: This folder includes a subfolder "Clean images" containing clean image data and a metadata file, *clean_meta*, with detailed socio-demographic and medical information for each participant in the clean set. Additionally, three CSV files for training, testing, and validation are provided, containing label information such as image quality, diagnostic label, severity grade, and more.
- Noisy: This folder includes a subfolder "Noisy images" containing noisy image data and a metadata file, *noisy_meta*, with detailed socio-demographic and medical information for each participant. A CSV file, *noisy_labels*, is also included, providing label information for each attribute.
- Unlabelled dataset: This folder includes a subfolder "Unlabelled images".
- A CSV file, "Region_annotation", is also included, containing the filenames and coordinate information of various regions within each image.

5 CatScreen Framework and Experimental Details

This section presents a detailed overview of the CatScreen Framework, aligning it with the mathematical problem formulation described in Section 2. It introduces two complementary modeling approaches, Struc-



(a)



(b)

Figure 4: Presents the two complementary frameworks: (a) structured sequential analysis framework for automated cataract screening and (b) Multitask learning framework where each label is jointly predicted for automated cataract screening.

tured Sequential Analysis and Multitask Learning, and provides descriptions of the evaluation protocols, baseline algorithms, and implementation specifics essential for validation of automated cataract screening solutions.

5.1 CatScreen Framework

The CatScreen Framework is designed to address the automated diagnostic tasks delineated mathematically in Section 2, specifically targeting the accurate prediction of clinically relevant attributes $A = (Q, T, D, C, G)$ from slit-lamp images I and patient metadata M. To achieve accurate and clinically interpretable predictions, it employs two paradigms: Structured Sequential Analysis and Multitask Learning, summarized in Table 3.

1. Structured Sequential Analysis: Figure 4a represents the Structured Sequential Analysis framework. This approach closely mimics the clinical reasoning of the doctors by explicitly modelling the depen-

dencies among diagnostic attributes. Each stage builds upon preceding predictions, reflecting the typical sequential decision-making of ophthalmologists.

Starting with a slit-lamp image (I), the model first assesses the image quality (Q) and illumination type (T). These are important as they directly affect the subsequent diagnostic predictions. Based on these intermediate assessments, the model then predicts the overall diagnosis (D) by combining it with patient metadata (M), determining whether the eye is normal, has a cataract or shows other conditions. If a cataract is detected, the model then proceeds to classify the cataract type and its severity grade. By sequentially building each prediction upon prior outputs, this approach facilitates explicit feature refinement and error control at each stage, aligning well with medical interpretability requirements.

Table 3: Comparison of Structured Sequential Analysis and Multitask Learning Frameworks for cataract screening.

Aspect	Structured Sequential Analysis	Multitask Learning
Approach	Sequential prediction with causal conditioning	Parallel prediction of all attributes
Architecture	Separate models per attribute	Shared backbone with task-specific heads
Advantages	Mimics clinical workflows, interpretable	Leverages inter-task correlations, efficient
Limitations	Higher computational cost	Less explicit causal modeling

2. Multitask Learning Framework: Figure 4b presents the multitask approach. Unlike the sequential approach, this framework predicts all the diagnostic attributes jointly from the same set of inputs. A shared feature encoder first extracts global representations from the slit-lamp image (I), enriched by patient metadata (M), thereby capturing visual and contextual information. Separate task-specific classification heads are then used to simultaneously predict image quality (Q), illumination type (T), diagnosis (D), cataract subtype (C), and severity grade (G). This parallel formulation allows the model to leverage correlations among tasks while avoiding explicit sequential dependencies, thus enabling efficient end-to-end learning. The overall training objective combines individual classification losses for each task into a composite loss function (as described in Equation 7), promoting shared representation learning while allowing specialization for each attribute.

5.2 Experimental Protocol and Baselines

To evaluate the effectiveness of these frameworks, rigorous experimental protocols and baseline assessments were developed, ensuring reliability, reproducibility, and generalizability.

5.2.1 Evaluation Protocol

Table 2a presents the distribution of available labels in the clean set. This part of the CatScreen dataset was partitioned into training, validation, and testing subsets following a 70:10:20 split. To maintain data integrity and avoid data leakage, partitioning was performed strictly at the patient level, ensuring all images from a single patient reside exclusively within one subset. Furthermore, balanced representation of diagnostic categories across all partitions was carefully maintained, reducing biases and ensuring robust model generalization across varied diagnostic scenarios.

5.2.2 Baseline Algorithms

Benchmark experiments were conducted using both Structured Sequential Analysis and Multitask Learning frameworks to establish foundational performance metrics. These baseline experiments focused solely on visual information from slit-lamp images, providing insights into the intrinsic discriminative power of the visual data alone, without integrating patient metadata.

Structured Sequential Analysis Baseline: In this setup, each diagnostic attribute — including image quality (Q), illumination type (T), overall diagnosis (D), cataract subtype (C), and severity grade (G)

is predicted independently using separate models, without explicitly cascading outputs from one stage to another. Instead of enforcing explicit sequential conditioning, each prediction implicitly captures relevant cues from the image that may be shared across attributes. For example, although severity and subtype are clinically related, no direct sequential dependencies are imposed during training; each model learns to internally extract latent information from the image that implicitly reflects these relationships. This design serves as a fundamental baseline to understand the inherent capacity of visual representations to support each task in isolation while still allowing the model to leverage potential cross-attribute signals implicitly embedded in the learned features.

Multitask Learning Baseline: In contrast, the multitask baseline jointly predicts all labels in a single end-to-end model. A common feature extractor first learns an overall representation from the slit-lamp image. Then, separate prediction heads work in parallel to estimate image quality (Q), illumination type (T), diagnosis (D), cataract subtype (C), and severity grade (G). The model is trained using a combined loss that balances each task, helping it learn shared information across tasks while allowing each prediction head to focus on its specific details. This formulation enables the model to exploit inter-task correlations more explicitly within a single unified architecture and supports rapid multi-attribute inference in a clinical setting.

For a comprehensive assessment, diverse deep learning architectures were employed, encompassing convolutional neural networks (CNNs) and transformer-based models. Specifically, models such as VGG-16 (Simonyan & Zisserman, 2015), ResNet18 (He et al., 2016), ResNet34 (He et al., 2016), MobileNet-V2 (Sandler et al., 2018), EfficientNet-B4 (Tan & Le, 2019), DenseNet-121 (Huang et al., 2017), swin transformer (swin_base_patch4_window_224) (Liu et al., 2021), and vision transformer (vit_base_patch16_224) (Dosovitskiy et al., 2021), all pretrained on the ImageNet dataset (Deng et al., 2009), were evaluated to benchmark model performance across different architectural paradigms. These were selected for their proven performance in image classification, balancing efficiency and feature extraction.

5.2.3 Implementation Details

All models were trained for 50 epochs using the AdamW optimizer with an initial learning rate of 0.0001 and a weight decay of 1×10^{-5}. Weighted cross-entropy loss was employed to mitigate class imbalances prevalent within ophthalmic datasets. Computational experiments were executed using PyTorch on a DGX workstation equipped with 256 GB RAM and four Nvidia V100 GPUs (each with 32 GB memory).

6 Results and Analysis

This section analyzes the baseline performance outcomes obtained using the Structured Sequential Analysis and Multitask Learning frameworks. The performance metrics used to evaluate these approaches include the F1 score, precision, and recall, providing an insight into each framework's strengths and limitations. Additionally, this section discusses key technical challenges identified during experimentation and elucidates how the CatScreen dataset contributes effectively toward mitigating these issues.

6.1 Structured Sequential Analysis

Table 4 summarizes the F1 scores for each diagnostic attribute across various popular deep learning backbone architectures utilized for medical imaging classification tasks. Complementing these results, Figure 5 visually illustrates the mean precision and recall achieved by each model, facilitating intuitive comparisons. The results consistently indicate an inverse correlation between the complexity of the classification task and model performance. For simpler classification tasks, such as illumination type classification, nearly all models achieved excellent F1 scores (0.90–0.98). Particularly, the *Diffuse* and *Direct Focal* illumination types were classified with very high confidence, reflecting their distinctive visual characteristics. However, the *Retro* illumination type showed marginally lower performance (0.90–0.93), possibly attributable to subtler visual cues and its similarity to direct focal illumination.

6.1.1 Image Quality Assessment

In the task of image quality assessment, the *Acceptable* class consistently achieved robust F1 scores ranging between 0.91 and 0.93. Conversely, *Good* and *Poor* categories showed significantly weaker performance, often with near-zero scores. This result highlights a notable data imbalance favoring the *Acceptable* class, emphasizing the need for data augmentation strategies or class-balanced loss functions to enhance model sensitivity towards minority classes.

6.1.2 Diagnostic Classification

Diagnostic classification demonstrated moderate-to-high accuracy across most models. The *Cataract* class notably exhibited high F1 scores (0.78–0.81), attributable to its distinct visual features and adequate representation in the dataset. In contrast, the *Normal* class showed relatively lower scores (0.60–0.66), reflecting the challenges of distinguishing early-stage cataracts from healthy eyes due to subtle visual overlaps. The *Others* category demonstrated strong performance (0.92–0.95) despite minor variations, suggesting some degree of heterogeneity in these conditions and highlighting opportunities for further data enrichment.

6.1.3 Cataract Type Classification

Cataract subtype classification proved significantly challenging due to subtle visual distinctions and class imbalance. *Pseudophakia (PP)* achieved consistently high F1 scores (0.88–0.93) due to its visually distinct characteristics. However, subtypes like *Posterior Subcapsular Cataract (PSC)* and *Cortical* performed poorly (F1 scores ranging from 0.00–0.32 and 0.13–0.52 respectively), highlighting difficulties arising from their subtle visual patterns and limited training data. The *Nuclear* subtype showed intermediate to strong performance (0.72–0.77), benefiting from central opacity features, while the *Others* subtype presented highly inconsistent results (0.10–0.21), primarily driven by data scarcity.

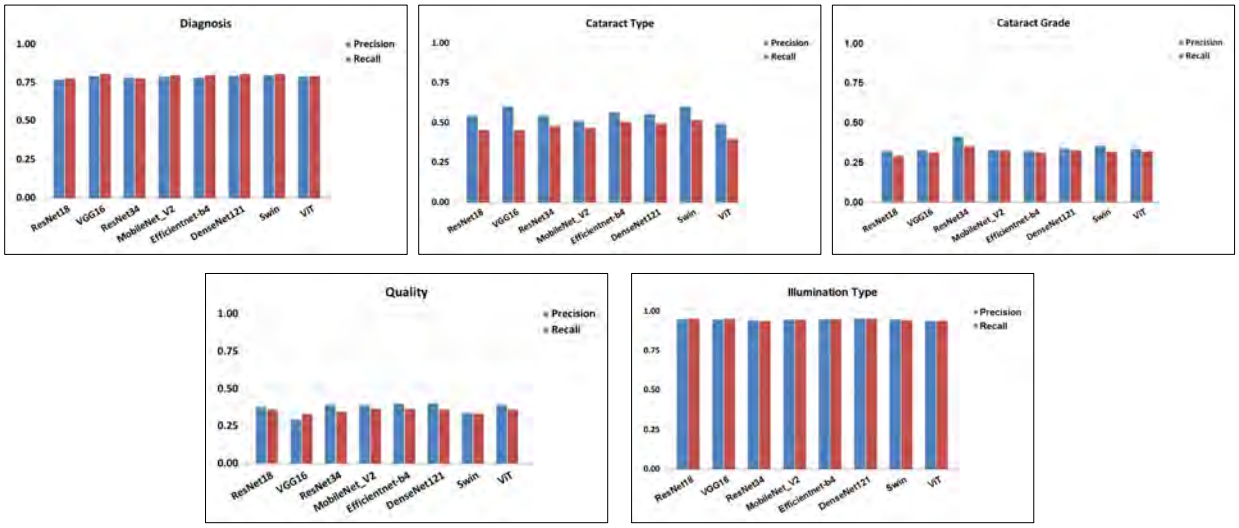


Figure 5: Showcasing the mean precision and recall across varying classification labels.

6.1.4 Cataract Severity Grading

Cataract severity grading emerged as particularly challenging, with *Severe* cases consistently showing poor F1 scores (0.15–0.28), reflecting significant class imbalance and limited representation. The *Not Applicable (NA)* category, representing non-cataract cases, achieved higher scores (0.76–0.80), and the *Mild* class produced moderate scores (0.65–0.70). These results emphasize the need for richer datasets that include adequate representation of severe cataract cases and advanced model architectures to accurately capture severe pathological patterns.

Models/Classes	Res18	VGG-16	Res34	M_V2	E-b4	D121	Swin	ViT
Quality								
Good	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.07
Acceptable	0.92	0.93	0.93	0.92	0.91	0.92	0.92	0.91
Poor	0.12	0.00	0.12	0.19	0.13	0.18	0.05	0.12
Illumination Type								
Diffuse	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Direct Focal	0.94	0.94	0.93	0.94	0.94	0.95	0.94	0.93
Retro	0.92	0.92	0.91	0.92	0.92	0.93	0.91	0.90
Diagnosis								
Normal	0.60	0.66	0.60	0.64	0.64	0.65	0.65	0.64
Cataract	0.78	0.79	0.80	0.79	0.79	0.80	0.81	0.81
Others	0.93	0.94	0.95	0.94	0.94	0.95	0.94	0.92
Cataract Type								
NA	0.61	0.62	0.67	0.64	0.62	0.63	0.67	0.58
Nuclear	0.74	0.74	0.77	0.75	0.74	0.75	0.75	0.72
Cortical	0.36	0.30	0.38	0.38	0.45	0.52	0.40	0.13
PSC	0.13	0.08	0.16	0.11	0.25	0.13	0.32	0.00
PP	0.91	0.92	0.92	0.91	0.90	0.92	0.93	0.88
Others	0.11	0.21	0.10	0.11	0.21	0.11	0.17	0.13
Cataract Grade								
NA	0.77	0.80	0.76	0.76	0.77	0.79	0.79	0.80
Mild	0.65	0.69	0.66	0.66	0.67	0.67	0.68	0.70
Severe	0.23	0.20	0.21	0.21	0.19	0.19	0.28	0.15

Table 4: F1 Score comparison of multiple labels across various backbones as feature extractors. (Here Res: ResNet, M_V2: MobileNet-V2, E-b4: EfficientNet-B4, D121: DenseNet121, PP: Pseudophakia, PSC: Posterior Subcapsular Cataract, NA: Not Applicable)

6.2 Multitask Learning Framework

Table 5 summarizes the F1 scores for each diagnostic attribute within the multitask learning framework, where multiple tasks are predicted simultaneously from shared visual representations.

6.2.1 Image Quality Assessment and Illumination Type Classification

In multitask learning, image quality prediction again showed robust performance in the *Acceptable* category (F1: 0.92–0.93). Conversely, the *Good* and *Poor* categories exhibited critically low performance (F1 near 0), highlighting persistent challenges due to class imbalance. Interestingly, Vision Transformer (ViT) demonstrated slight improvement in the *Poor* category (F1: 0.10), emphasizing the potential of transformer architectures for capturing subtle visual differences. Further, illumination type classification demonstrated exceptional performance across all models, achieving nearly perfect scores for the *Diffuse* category (F1: 0.98). Strong performances were also recorded for *Direct Focal* and *Retro* illumination classes, with F1 scores ranging from 0.90 to 0.95, highlighting the consistency and reliability of models in handling clearly distinguishable visual features.

6.2.2 Diagnostic Classification and Cataract Type Classification

Diagnostic classification within the multitask framework again yielded strong outcomes for the *Cataract* (F1: 0.79–0.82) and *Others* (F1: 0.91–0.94) classes, reflecting their visually distinct and adequately represented nature. The *Normal* category continued to pose challenges (F1: 0.60–0.67), reiterating difficulties in differentiating healthy from early pathological states due to subtle visual overlaps. Next, subtype classification presented considerable challenges within the multitask framework. The *Pseudophakia (PP)* and *Nuclear* cataract classes showed commendable performances (F1: 0.87–0.92 and 0.74–0.78, respectively). In contrast,

Models/Classes	Res18	VGG-16	Res34	M_V2	E-b4	D121	Swin	ViT
Quality								
Good	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Acceptable	0.93	0.93	0.93	0.92	0.93	0.93	0.93	0.93
Poor	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10
Illumination Type								
Diffuse	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Direct Focal	0.95	0.94	0.93	0.94	0.93	0.94	0.94	0.94
Retro	0.92	0.92	0.92	0.92	0.90	0.91	0.92	0.91
Diagnosis								
Normal	0.63	0.66	0.64	0.63	0.60	0.65	0.67	0.66
Cataract	0.79	0.81	0.80	0.80	0.79	0.80	0.80	0.82
Others	0.91	0.91	0.92	0.89	0.91	0.92	0.94	0.92
Cataract Type								
NA	0.65	0.66	0.63	0.64	0.61	0.65	0.67	0.67
Nuclear	0.76	0.75	0.76	0.76	0.74	0.76	0.75	0.78
Cortical	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50
PSC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PP	0.90	0.92	0.89	0.87	0.89	0.91	0.92	0.91
Others	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cataract Grade								
NA	0.79	0.80	0.78	0.78	0.78	0.79	0.81	0.81
Mild	0.69	0.71	0.69	0.71	0.70	0.70	0.71	0.74
Severe	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0.09

Table 5: F1 Score comparison of multiple labels across various backbones as feature extractors for multitask learning approach. (Here Res: ResNet, M_V2: MobileNet-V2, E-b4: EfficientNet-B4, D121: DenseNet121, PP: Pseudophakia, PSC: Posterior Subcapsular Cataract, NA: Not Applicable)

the *Cortical*, *PSC*, and *Others* subtypes consistently yielded near-zero scores, emphasizing the limitations imposed by subtle visual differences, insufficient data, and high intra-class variability. The ViT architecture, however, demonstrated notable improvement for the *Cortical* subtype (F1: 0.50), confirming the potential of transformer-based models in fine-grained classification tasks.

6.2.3 Cataract Severity Grading

Severity grading results mirrored challenges observed in the sequential analysis. The *Not Applicable (NA)* and *Mild* classes performed reasonably well (F1: 0.70–0.81), while the *Severe* category remained problematic with consistently poor scores (near-zero F1 scores). The slight improvement observed in the *Severe* category by ViT (F1: 0.09) further supports transformer architectures' capability to manage complex visual variations better than traditional models.

6.3 Comparative Model Analysis

Overall, transformer-based models such as Vision Transformer (ViT) and Swin Transformer consistently exhibited superior or comparable performance across challenging tasks requiring subtle visual differentiation. Specifically, transformer architectures demonstrated notable strengths in capturing nuanced textural differences, such as those observed in cortical cataracts and other fine-grained pathological conditions. These architectures excelled due to their attention-based mechanisms, enabling models to focus dynamically on regions of interest that are clinically relevant yet visually subtle. In contrast, traditional convolutional neural network architectures such as ResNet and VGG demonstrated robust results predominantly on well-represented classes with clear and distinct visual features, but consistently struggled with fine-grained classification and minority classes. The performance disparity arises primarily due to the inherent design of CNNs, which em-

phasizes local spatial features and tends to overlook subtle global context required for differentiating visually similar conditions.

These performance patterns clearly illustrate the inherent complexity associated with fine-grained medical image classification, especially in ophthalmic diagnostics. Anatomically, certain cataract types—such as the spoke-like opacities characterizing cortical cataracts or the subtle granular patterns indicative of posterior subcapsular cataracts pose substantial challenges for current CNNs and even transformer-based models. Furthermore, the significant feature overlap between normal eyes and early-stage cataract conditions exacerbates the challenge of establishing distinct decision boundaries, often resulting in diagnostic ambiguity. From a clinical perspective, these results highlight the necessity for more sophisticated representation learning methodologies that can reliably identify subtle pathological characteristics inherent in fine-grained ophthalmic classification scenarios. Effective solutions may require augmenting visual models with patient-specific contextual information, such as socio-demographic features, diabetic conditions, or detailed ocular history, to achieve more informed and accurate diagnostic predictions.

6.4 Technical Challenges and CatScreen's Contributions

Our findings identify several promising directions for future research to address current limitations. Leveraging self-supervised pretraining techniques can enhance models' abilities to extract meaningful features from unlabeled ophthalmic data. Moreover, integrating advanced attention mechanisms and multi-scale feature refinement strategies could significantly boost model sensitivity to subtle visual distinctions, critical for effective fine-grained classification. These methods can help models better discriminate between visually similar ophthalmic conditions, ultimately leading to more robust, interpretable, and clinically reliable diagnostic outcomes.

The multitask learning framework specifically requires careful balancing between shared representations and task-specific fine-tuning to mitigate negative transfer and improve overall task performance. Implementing dynamic task-weighting or uncertainty-based loss re-weighting strategies could address these challenges effectively. Conversely, the structured sequential analysis framework would benefit from explicitly modeling inter-task dependencies. Figure 6 showcases the sample result images with true and predicted labels that are misclassified due to poor-quality images. In sequential causal models, early-stage errors cascade forward and cause misclassifications in subsequent tasks that depend on these intermediate predictions. This emphasizes the critical need for robust handling of quality variations to mitigate cascading errors in sequential decision models. Approaches such as cascaded conditioning, multi-stage refinement modules, or cross-task attention mechanisms could leverage shared clinical features while maintaining modularity and improving diagnostic accuracy.

Future research will explore the explicit evaluation of incorporating patient metadata, such as demographics and clinical histories, alongside visual data, potentially enhancing diagnostic accuracy and clinical applicability. Additionally, addressing class imbalance using techniques like data augmentation, synthetic oversampling, or focal loss methods could significantly improve sensitivity to minority classes, particularly severe cataract cases and extreme image quality categories. Further research into advanced attention mechanisms, ensemble approaches, or hierarchical classification strategies specifically targeted toward challenging cataract subtypes, such as Cortical and PSC, could better capture nuanced visual distinctions. Lastly, explicitly evaluating model robustness through the noisy-labeled subset by leveraging semi-supervised and robust learning approaches would enhance real-world generalizability and reliability.

To support these research directions effectively and address identified technical challenges, CatScreen provides several key contributions and innovative features:

- **Class Imbalance and Minority Class Performance**: Both SCM and MTL frameworks exhibited significantly reduced performance on minority classes. CatScreen addresses this issue by preserving realistic class distributions, thereby facilitating the development of models robust to real-world class imbalances.
- **Fine-grained Classification**: Differentiating subtle visual distinctions among cataract subtypes and severity levels remains challenging. CatScreen's fine-grained annotations and precise labeling

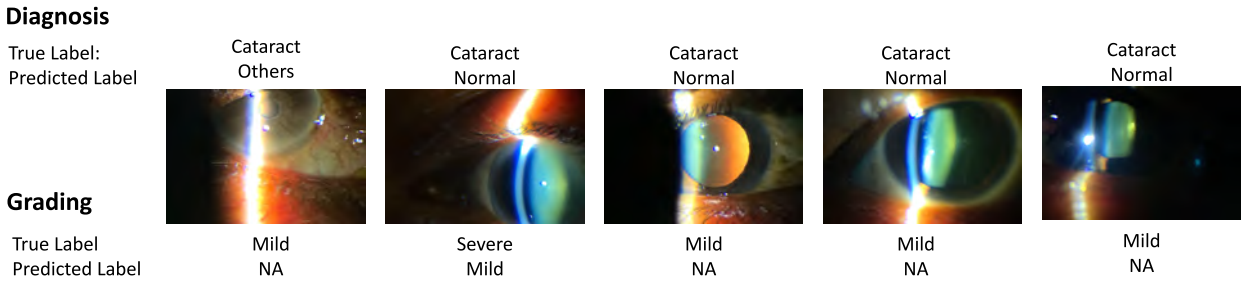


Figure 6: Presents the sample result images of poor-quality images causing misclassification across diagnosis and severity grade labels

enable models to learn nuanced, clinically meaningful distinctions, thus enhancing interpretability and diagnostic accuracy.

- **Robustness to Annotation Noise**: Clinical datasets inherently contain annotation inaccuracies. CatScreen includes a Noisy Set specifically designed to develop and evaluate models robust against imperfect annotations, thus aligning more closely with real-world clinical practice.
- **Utilizing Unlabelled Data for Enhanced Representation Learning**: To boost generalization and robustness, CatScreen offers a substantial Unlabelled Set. This set supports the development of self-supervised, semi-supervised, and active learning techniques, enabling models to utilize extensive unlabeled data for improved feature extraction and stronger generalization.

7 Conclusion

CatScreen advances ophthalmic diagnostics by offering a richly annotated, large-scale slit-lamp image dataset tailored specifically for addressing real-world challenges in cataract screening. It captures a comprehensive range of clinically relevant annotations, including image gradability, illumination types, cataract subtypes, and severity grades, enabling the creation of highly interpretable and clinically meaningful AI solutions. Beyond traditional supervised learning, CatScreen dataset uniquely incorporates noisy-labelled and unlabeled data subsets, thereby facilitating research into robust self-supervised and semi-supervised learning strategies reflective of practical clinical scenarios. The detailed patient metadata further enhances its utility by supporting the integration of holistic clinical contexts into diagnostic models. Additionally, this work presents two complementary AI frameworks, Structured Sequential Analysis and Multitask Learning, each offering distinct yet synergistic approaches toward enhancing model interpretability and efficiency. By addressing crucial challenges such as class imbalance, subtle visual distinctions among cataract types, annotation noise, and the effective utilization of unlabeled data, CatScreen establishes a strong foundation for developing robust, accessible, and clinically reliable cataract screening tools. We anticipate that CatScreen will inspire extensive innovation, significantly accelerating the adoption of AI-driven eye care solutions and improving global cataract screening and management.

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