Precise Lens Status Classification via Projection Tuning for Efficient Adaptation to Data Shifts in Small Cataract Image Datasets

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Abstract

Cataract is the leading cause of blindness worldwide. Access to cataract screening is important to enable treatment and vision restoration to eliminate avoidable blindness. This paper introduces an artificial intelligence (AI)-driven approach designed to improve access to cataract screening, using external ocular images captured by community health workers utilizing a smartphone-based anterior segment eye imaging modality. The platform integrates segmentation and classification networks by leveraging pretrained foundation models to accurately differentiate between healthy eyes, immature cataracts, and mature cataracts. We evaluated several fine-tuning strategies and proposed *projection tuning* as an efficient and lightweight approach to tackle distribution shift challenges among datasets. In combination with a Vision Transformer model, we demonstrate exceptional lens classification performance using a small cataract image database. Our investigation confirms that our smartphone-based imaging system combined with the proposed framework offers a effective and accurate solution for cataract detection, addressing distribution shift challenges.

1 Introduction

Cataract remains the leading cause of blindness worldwide, and early detection paired with timely medical intervention can greatly enhance visual acuity and overall quality of life [1, 2]. Recently, there has been growing interest in application of artificial intelligence (AI) to automate diagnosis of various ophthalmic conditions through clinical images with foundational models, initially trained on large image datasets, being fine-tuned for downstream medical image tasks [3, 4, 5, 6]. This is particularly important in low resource settings or rural areas where access to an optometrist or ophthalmologist may be limited [7, 8].

The growing trend of utilizing vast amounts of data with foundation models (FMs) has achieved success in general domains. However, in specialized fields like healthcare, the availability of high-

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quality data is often limited, making it challenging for these models to perform effectively. Moreover, the complexities of nuanced medical tasks demand expert knowledge that general models may struggle to incorporate [9, 10]. Therefore, an effective fine-tuning strategy becomes essential to adapt these models to the unique demands of specialized domains like healthcare, ensuring they can accurately and efficiently leverage the available data.

In situations where data is scarce and complex, common strategies include data purification to improve its quality and relevance, as well as synthesizing additional data to expand the training set [11, 12]. However, these preprocessing methods often fall short in providing a comprehensive representation of the data distribution, and the use of synthetic images can negatively impact model performance [13].

Another approach is fine-tuning the model to better capture domain-specific features [14, 15]. This involves updating all the parameters during training or selectively fine-tuning the last few layers while keeping the earlier layers frozen. However, updating all the weights is often computationally constrained on mobile devices, and fine-tuning only the later layers may lead to vulnerability to data shifts and overfitting, as these topmost layers hold semantic information crucial for decision-making [16, 17]. To address these challenges, we introduced *projection tuning* within the pre-trained Vision Transformer (ViT) model [18]. In the ViT, images are divided into patches, and these flattened patches undergo a linear projection. These projections are then combined with class and position embeddings before being processed by the Transformer encoder block. We hypothesized that projection tuning would enable the ViT model to outperform other fine-tuning strategies, particularly in scenarios of data scarcity and distribution shifts, as it focuses on fine-tuning the linear projection step, which occurs in the earlier layers of the model.

To date, AI-driven, automated diagnostic technologies primarily rely on data acquired by skilled ophthalmologists using specialized imaging modalities in healthcare settings, such as slit lamp or fundus imaging. Although deep learning systems have been developed to accurately identify diseases like diabetic retinopathy [2, 19], glaucoma [20, 21], and cataract[22, 23], the potential to utilize external ocular images from accessible portable, handheld devices has not been widely explored. To overcome these limitations, our dataset was collected by community health workers in Southern India using a inexpensive, smartphone-based anterior segment eye imaging system that we developed. Due to ongoing developments and upgrades to the imaging system during the data collection period, we obtained two datasets that share similarities while exhibiting subtle differences (lighting, hue, magnification, resolution), leading to a domain shift problem that we sought to address in this study.

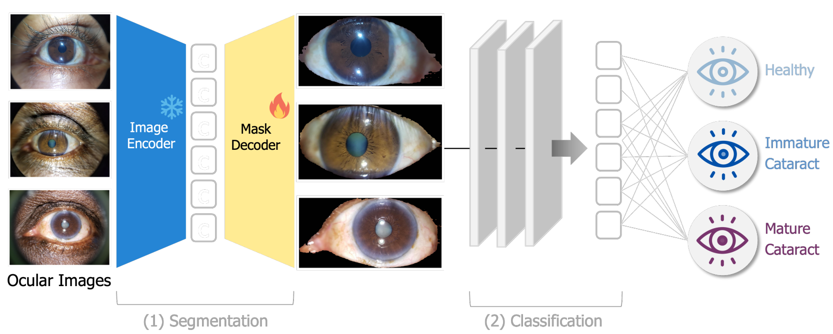


Figure 1: Deep learning framework for cataract diagnosis

In summary, our contribution include:

- Develop an AI platform that utilizes anterior segment images captured by a smartphone-based imaging modality, integrating a foundational model for precise segmentation and classification of lens status.
- Investigate various deep learning architectures and fine-tuning strategies to demonstrate the effectiveness of these approaches in enhancing model performance across datasets.
- Propose a projection tuning method and demonstrate its capability to robustly predict disease status across two cohorts, even with data distribution shifts caused by different hardware designs and issues related to data scarcity.

2 Methods

2.1 Dataset and ethics statement

After obtaining informed consent, community health workers collected smartphone-based eye images of patients attending community eye screenings. Diagnosis labels for each image were obtained using ophthalmologists' clinical diagnoses made via pen light examination at the same screening. The study was approved by the Institutional Review Boards of Aravind Eye Hospital and the Johns Hopkins University School of Medicine.

Smartphone-based anterior segment eye images were gathered in real-world conditions by community health workers at the Aravind Eye Hospital in Tamil Nadu, India using two distinct hardware designs. The first dataset (i.e., $\texttt{CATARACT}_1$) consists of 2,324 images collected using a Samsung M21, including 954 healthy eyes with a clear crystalline lens, 1,054 immature cataracts, and 316 mature cataracts. The second dataset (i.e., $\texttt{CATARACT}_2$) consists of 1,521 images captured with a Samsung S8, including 383 healthy eyes, 985 immature cataracts, and 153 mature cataracts. The primary differences between these datasets are the magnification, type of lighting, and lighting orientation due to differences in design of the hardware imaging systems attached to the Android phones. Representative images from both datasets of each lens status class are shown in Figure 2.

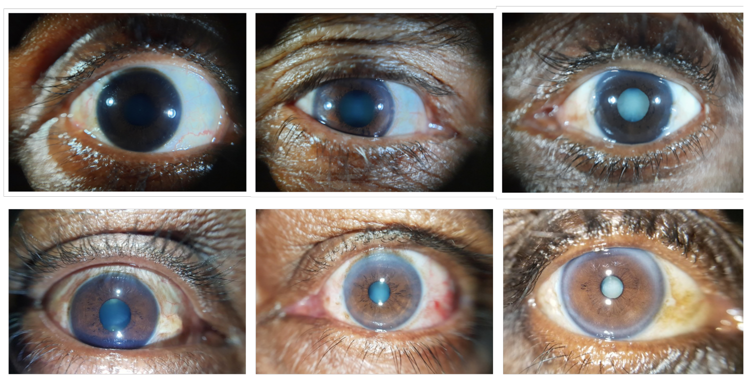


Figure 2: Representative images from the $\texttt{CATARACT}_1$ and $\texttt{CATARACT}_2$ datasets
The top row represents the $\texttt{CATARACT}_1$ dataset, while the bottom row corresponds to the $\texttt{CATARACT}_2$ dataset. The first column displays healthy eyes, the second column shows immature cataracts, and the third column presents mature cataracts with clear differences in lens status.

2.2 Development of a two-stage deep learning framework

As illustrated in Figure 1, the entire process involves (1) segmentation networks to refine images and (2) classification networks to distinguish between healthy eyes, immature cataracts, and mature cataracts labeled with gold standard ophthalmologist diagnoses.

To fine-tune segmentation models, a dataset of 1,000 randomly selected images was manually annotated with polygonal shapes to accurately delineate the regions of interest. We employed the recently developed FM, Segment Anything (SAM) [24], to explore the effectiveness of large FMs for segmentation in a specialized biomedical use case. These annotated images were then used for model training. The models were trained only on the $\texttt{CATARACT}_1$ dataset to refine their ability to accurately segment relevant areas, including sclera, iris, and pupil. The training process optimized the models using backpropagation with Dice loss. Image augmentation was unnecessary to achieve a 0.95 Dice score, and only the decoder was fine-tuned while the encoder remained frozen.

The segmented images were randomly split at a 7:1.5:1.5 ratio for training, validation, and testing of a fine-tuned deep learning models. No overlap was allowed among training, validation, and testing sets. We also implemented 5-fold cross-validation, a method that helps mitigate biases associated with hyperparameter tuning and algorithm selection.

For classification networks, this study explored the performance of four CNN models (VGG-11 [25], ResNet-18 [26], MobileNetV2 [27], EfficientNet B0 [28]) and five Transformer models (DeiT-Ti, DeiT-distilled [29], MobileViT-S [30], EfficientFormer-L1 [31], ViT-base [18]). Each model was initialized with pre-trained ImageNet [32] weights to enhance performance.

During training, we applied image transformations and augmentations, such as random horizontal flips and Gaussian blur, to improve model generalization. Image standardization and normalization were consistently applied across both training and testing phases to ensure uniformity in data processing.

We utilized the PyTorch deep learning framework [33] (version 2.0.1) for model training with one NVIDIA RTX A5500. The models were trained using backpropagation, with batch sizes of 256 images for CNN models and 8 images for Transformer models. We employed the Adaptive Moment Estimation (ADAM) optimizer [34] with a learning rate set to 1×10^{-4}. The cross-entropy loss function was applied as the objective function for the classification tasks, ensuring the models were optimized effectively for accuracy. The code will be released upon publication.

2.3 Projection tuning

This section outlines a brief overview of how ViT works and presents the projection tuning, designed to optimize the ViT model for efficient fine-tuning and to address the distributional differences between datasets (Figure 4).

Consider an image of resolution H and W with C number of channels. ViT divides each input image into a grid of patches, where each patch is of size $p \times p$ and the total number of patches is $N = \frac{H \times W}{p^2}$ [2]. These patches are then flattened into vectors, resulting in a sequence of patch vectors: $\{\mathbf{x}_i\}_{i=1}^{N}$. Each patch vector $\mathbf{x}_i \in \mathbb{R}^{\times(p^2 \cdot C)}$ is linearly projected into a D-dimensional token embeddings $\mathbf{z}_{0i}$, using a learnable linear projection $\mathbf{E} \in \mathbb{R}^{(p^2 \cdot C) \times D}$. These token embeddings $\{\mathbf{z}_{0i}\}_{i=1}^{N}$ serve as input to the Transformer encoder, which produce the final classification predictions. For more detailed information, please refer to the original paper [18].

Our projection tuning approach solely fine-tunes the linear projection matrix, E, while all other layers are kept frozen. The core idea behind the proposed method is to decouple the module that maps pixel inputs to vector representations (i.e., patcher) from the one that performs actual classification based on these representations. In this framework, the Transformer encoder – which can be regarded as the reasoning and decision-making module – is shared across different datasets, while the fine-tuning stage focuses on effectively aligning input representations.

3 Results

3.1 Segmentation and classification using the $\texttt{CATARACT}_1$ dataset

3.1.1 The effect of segmentation on classification

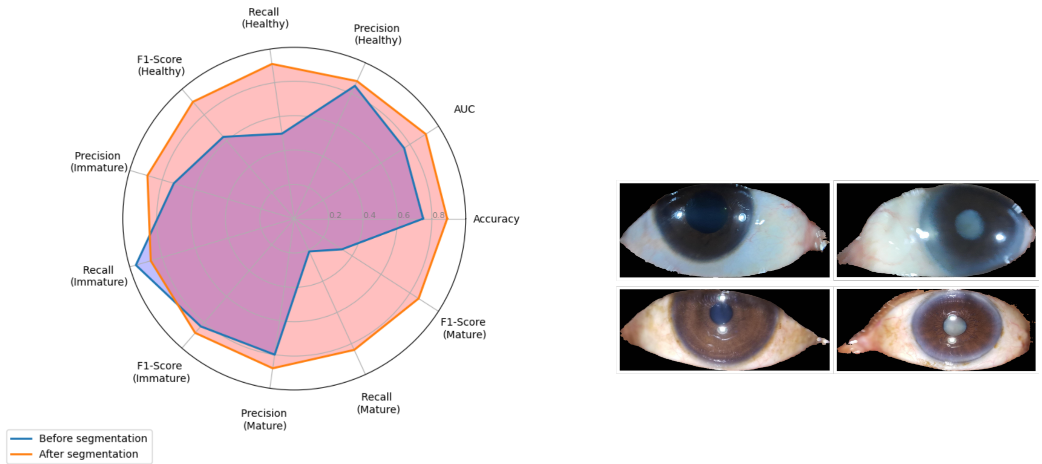
Our two-stage deep learning framework for cataract diagnosis starts with a segmentation module. Segmentation is performed before classification for two key reasons: (1) medical imaging modalities typically exhibit high complexity and dimensionality relative to the dataset size, and (2) our datasets consisted of images captured using a portable imaging system in real-world settings rather than controlled clinical environments, leading to increased variability. Inspired by iris preprocessing procedures used in biometric applications and acknowledging the advantages of minimized skin area and increased focus on the eye in images, we applied segmentation to standardize the images.

We fine-tuned SAM and utilized it for subsequent analyses. As discussed in Section 2.2, the fine-tuning was performed exclusively using the $\texttt{CATARACT}_1$ dataset. Additional fine-tuning with the $\texttt{CATARACT}_2$ dataset was not necessary to achieve comparable segmentation performance.

We employed convolutional neural network models, such as Very Deep Convolutional Networks 11 (VGG-11), Residual Networks 18 (ResNet-18), MobileNet, and EfficientNet, for the classification module (Section 3.1.2). When using the unsegmented whole images, the classification accuracy with ResNet-18 was 75%. After applying segmentation, the classification performance improved by 14%, resulting in an overall performance of 89% (Figure 3). Specifically, for mature cataract classification, which is the minority class among the three, the recall was 21% during testing. However,

[2] H and W are pre-adjusted to be multiples of p

after segmentation, the recall for the mature cataract class increased to 84%. This indicates that segmentation positively impacts overall classification performance by preprocessing the images and effectively guiding the model to focus on relevant anatomical regions, such as the pupil, rather than the features surrounding the eye.



(a) (b)

Figure 3: Comparison of segmentation effects (a) with example images (b).

3.1.2 Quantitative analysis of classification performance

Following the segmentation module, the models generate a binary mask to extract the region of interest. Using this mask, we selected pixel values within the targeted area while assigning zero values to the unwanted regions. Once the image preprocessing was complete, the segmented images were used in the classification module. We fine-tuned all layers to conduct tests using both Convolutional Neural Network (CNN) and Transformer models for this classification task.

In previously published papers focused on diagnosing eye diseases using deep learning approaches, models such as VGG, ResNet, MobileNet, Densely Connected Convolutional Networks (DenseNet), and their variations were commonly used [35, 36, 37, 38, 39]. However, using models with a large number of parameters relative to the dataset size can lead to overfitting and reduced performance. Therefore, we conducted tests using CNN models, including VGG-11, ResNet-18, MobileNetV2, and EfficientNet B0. These models are known for having relatively fewer parameters within their variants, which helps mitigate the risk of overfitting when fine-tuning on smaller datasets. Moreover, their lightweight nature makes them well-suited for future deployment on mobile devices. We also evaluated Transformer models, such as DeiT-Ti, DeiT-distilled, MobileViT-S, EfficientFormer-L1, and Vision Transformer (ViT-base). Transformer models are particularly effective at capturing long-range dependencies in data through self-attention and are efficient in processing inputs due to their ability to parallelize computations. CNN and Transformer model performance are shown in Table 1.

Accuracy results for the CNN models were as follows: VGG-11: 84%; ResNet-18: 89%; MobileNetV2: 86%; EfficientNet B0: 86%. ResNet-18 consistently outperformed the other CNN models across other evaluation metrics, including precision, recall, F1-score, and AUC. For the Transformer models, the accuracy outcomes were as follows: DeiT-Ti: 87%; DeiT-distilled: 88%; MobileViT-S: 88%; EfficientFormer-L1: 87%; ViT-base: 90%. Among these models, ViT-base consistently delivered the highest performance across diverse evaluation metrics.

Transformers generally outperformed CNN models across several evaluation metrics and proved to be more efficient in terms of training time. While CNN models needed at least 20 epochs to reach the desired performance, Transformer models achieved comparable results in 5 epochs, highlighting their efficiency in both training and inference.

Table 1: Comparison of classification performance after segmentation. Light green cells indicate the best performance among CNN models, and light blue cells indicate the best performance among Transformer models. (AUC: Area Under the Curve)

Model	Class	Accuracy	Precision	Recall	F1-score	AUC
VGG-11	Healthy	0.84 ± 0.02	0.84 ± 0.01	0.85 ± 0.02	0.85 ± 0.02	0.86 ± 0.01
	Immature Cataract		0.83 ± 0.02	0.84 ± 0.03	0.84 ± 0.02	
	Mature Cataract		0.82 ± 0.05	0.79 ± 0.07	0.80 ± 0.05	
ResNet-18	Healthy	0.89 ± 0.01	0.88 ± 0.03	0.91 ± 0.02	0.90 ± 0.02	0.91 ± 0.01
	Immature Cataract		0.89 ± 0.02	0.87 ± 0.03	0.88 ± 0.01	
	Mature Cataract		0.88 ± 0.04	0.84 ± 0.05	0.86 ± 0.03	
MobileNetV2	Healthy	0.86 ± 0.01	0.87 ± 0.03	0.88 ± 0.03	0.88 ± 0.02	0.88 ± 0.01
	Immature Cataract		0.85 ± 0.03	0.86 ± 0.03	0.86 ± 0.01	
	Mature Cataract		0.84 ± 0.05	0.79 ± 0.07	0.81 ± 0.05	
EfficientNet B0	Healthy	0.86 ± 0.02	0.87 ± 0.02	0.87 ± 0.02	0.87 ± 0.02	0.88 ± 0.01
	Immature Cataract		0.86 ± 0.02	0.87 ± 0.03	0.86 ± 0.02	
	Mature Cataract		0.82 ± 0.05	0.81 ± 0.03	0.81 ± 0.02	
DeiT-Ti	Healthy	0.87 ± 0.01	0.88 ± 0.03	0.89 ± 0.04	0.88 ± 0.01	0.89 ± 0.01
	Immature Cataract		0.86 ± 0.02	0.87 ± 0.05	0.86 ± 0.02	
	Mature Cataract		0.89 ± 0.07	0.81 ± 0.05	0.84 ± 0.02	
DeiT-distilled	Healthy	0.88 ± 0.01	0.88 ± 0.01	0.90 ± 0.02	0.89 ± 0.00	0.90 ± 0.01
	Immature Cataract		0.87 ± 0.02	0.88 ± 0.01	0.87 ± 0.01	
	Mature Cataract		0.87 ± 0.01	0.81 ± 0.04	0.84 ± 0.03	
MobileViT-S	Healthy	0.88 ± 0.01	0.89 ± 0.02	0.89 ± 0.02	0.89 ± 0.02	0.90 ± 0.01
	Immature Cataract		0.87 ± 0.02	0.88 ± 0.02	0.87 ± 0.01	
	Mature Cataract		0.87 ± 0.02	0.84 ± 0.08	0.85 ± 0.05	
EfficientFormer-L1	Healthy	0.87 ± 0.01	0.86 ± 0.02	0.91 ± 0.02	0.89 ± 0.01	0.89 ± 0.01
	Immature Cataract		0.88 ± 0.02	0.86 ± 0.02	0.87 ± 0.01	
	Mature Cataract		0.87 ± 0.03	0.81 ± 0.04	0.84 ± 0.03	
ViT-base	Healthy	0.90 ± 0.02	0.90 ± 0.02	0.92 ± 0.01	0.91 ± 0.02	0.91 ± 0.02
	Immature Cataract		0.89 ± 0.01	0.90 ± 0.01	0.89 ± 0.01	
	Mature Cataract		0.92 ± 0.03	0.83 ± 0.07	0.87 ± 0.04	

3.2 Impact of data distribution shifts on classification

As previously discussed, our two datasets are largely similar but display subtle differences due to variations in magnification and lighting. To visually capture these differences in the datasets, we plotted pixel value histograms, normalizing them to display the probability density, as shown in Figure 4. This analysis was conducted using segmented images, excluding the masked areas around the eye, which accounted for approximately 30% of all pixels. In the $\texttt{CATARACT}_1$ dataset, a significant pixel value peak was observed near 50, with a large concentration of values at 255. In contrast, the $\texttt{CATARACT}_2$ dataset exhibited a similar peak around 70, with a reduced frequency of pixel values above 160.

To assess the impact of these differences, we first performed zero-shot inference on the images from the $\texttt{CATARACT}_2$ dataset using deep learning models that were fine-tuned on the $\texttt{CATARACT}_1$ dataset. As in Table 2, this resulted in performance decline across both CNN and Transformer models. For CNN models, the performance decreased by up to 35%, with an average drop of 29%. Transformer models experienced a maximum performance drop of 39% and an average decrease of 29.4%.

When the two datasets were combined and models fine-tuned from scratch (mixed-dataset tuning), the performance of CNN models dropped by about 2-5%, while Transformer models exhibited a 1-2% decline. Additionally, when both CNN and Transformer models were fully fine-tuned on the $\texttt{CATARACT}_2$ dataset (full tuning), they maintained performance levels comparable to those achieved with the $\texttt{CATARACT}_1$ dataset.

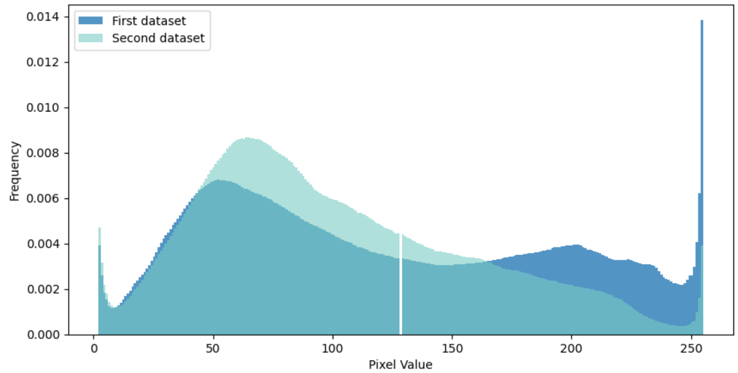


Figure 4: Density distribution plots for the $\texttt{CATARACT}_1$ and $\texttt{CATARACT}_2$ datasets.

Table 2: Accuracy comparison using the $\texttt{CATARACT}_2$ dataset across different tuning strategies.

Model	Zero shot	Mixed-dataset tuning	Full tuning
VGG-11	50%	82%	84%
ResNet-18	61%	84%	85%
MobileNetV2	67%	83%	84%
EfficientNet B0	51%	83%	83%
DeiT-Ti	58%	86%	83%
DeiT-distilled	63%	86%	84%
MobileViT-S	70%	87%	86%
EfficientFormer-L1	48%	85%	87%
ViT-base	54%	88%	86%

3.3 Projection tuning

As described in Section 2.1, the $\texttt{CATARACT}_1$ dataset consists of 2,324 images, while the $\texttt{CATARACT}_2$ dataset consists of 1,521 images. The differences in the style and distribution of these datasets led to a decline in classification performance (Table 2). The distribution shift and the smaller size of the $\texttt{CATARACT}_2$ dataset likely contributed to the difficulty in capturing the general representations necessary for accurate diagnosis, further impacting performance. These findings highlight the need for fine-tuning with a limited amount of new data and aligning features between the two datasets to improve classification accuracy and overall model robustness.

We focused on the ViT-base model due to its superior performance and resilience, as detailed in Sections 3.1.2 and 3.2. In the ViT-base architecture, image patches are linearly projected and flattened into patch embeddings before being fed into the Transformer encoder (Section 2.3). We explored four approaches to fine-tune this model: (1) fine-tuning all layers with the new dataset, (2) fine-tuning only the last layer, (3) low-rank adaptation (LoRA) [40], and (4) fine-tuning the projection layer.

LoRA is a parameter-efficient transfer learning approach, specifically tailored to enhance the effectiveness of fine-tuning large pre-trained models. By decomposing weight updates into low-rank matrices, it allows for the efficient adaptation of extensive neural networks to specific tasks while significantly reducing the number of trainable parameters without compromising overall performance. In our study, we used the ViT-base model as the backbone and focused solely on fine-tuning the LoRA adapters, targeting the query, key, and value modules of the self-attention mechanism. We set the alpha scaling parameter for LoRA to 16 and evaluated ranks of 2, 4, 8, and 16 to compare the results.

When using the complete set of updated images for training and validation, projection tuning achieved a performance of 81%, training from scratch resulted in 85%, and fine-tuning the last layer also yielded 76% (Figure 5). However, projection tuning demonstrated superior performance compared to the other methods when working with smaller datasets. For example, with only 10% of the dataset, projection tuning achieved 77% performance, whereas training from scratch resulted in 73%, and

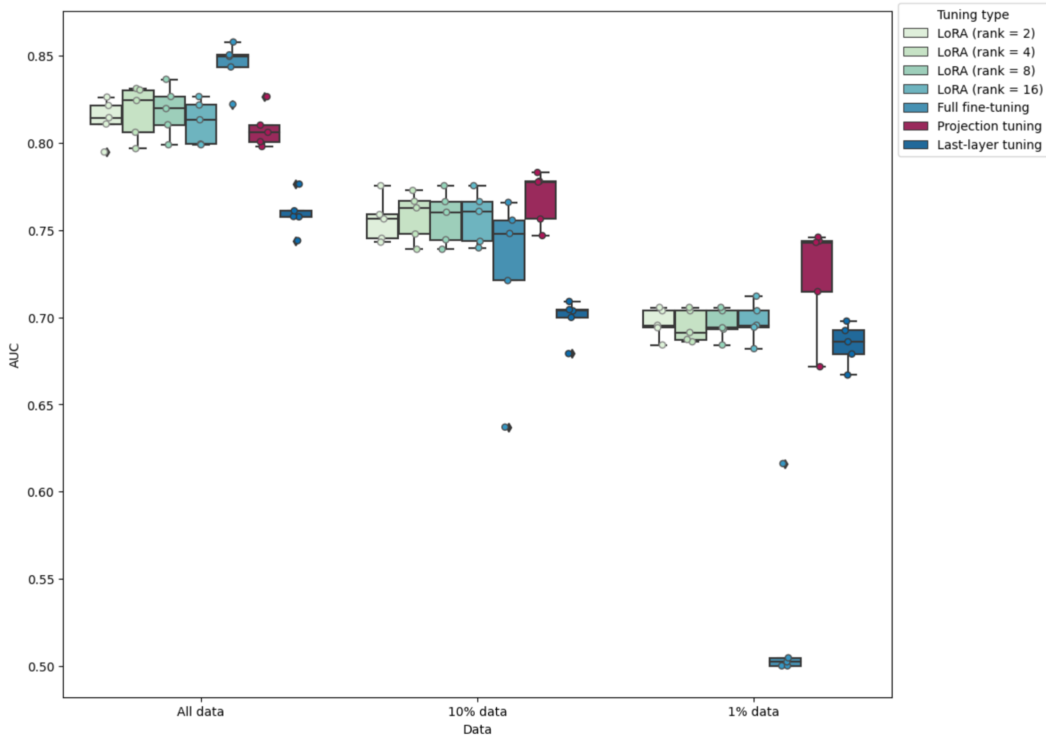


Figure 5: Schematic illustration of projection tuning and its outcomes compared to other fine-tuning methods, including full-layer fine-tuning, last-layer fine-tuning, and LoRA.

fine-tuning the last layer produced 70%. With just 1% of the dataset, projection tuning reached 72% performance, compared to 52% for training from scratch and 69% for fine-tuning the last layer.

In Figure 5, LoRA fine-tuning exhibited a consistent pattern relative to the rank size. As the size of the fine-tuning dataset decreased, LoRA's performance also declined. When using the full dataset, LoRA achieved an AUC between 81% and 82%. With 10% of the dataset, the AUC dropped to 76%, and with just 1% of the dataset, performance ranged from 69% to 70%. In comparison, projection tuning outperformed LoRA by 1% with 10% of the dataset, and by 2% to 3% with 1% of the dataset. Moreover, although LoRA requires fewer parameters to adjust compared to projection tuning, its floating point operations per second (FLOPS) is higher (Table 3). In terms of FLOPS, projection tuning, with its lower computational demands, is more efficient and better suited for resource-constrained environments, such as mobile devices or real-time systems.

To further analyze the differences in feature representation depending on the fine-tuning strategies, we conducted principal component analysis (PCA). Using the ViT-base model, initialized with the pretrained $\texttt{CATARACT}_1$ dataset and then fine-tuned with the $\texttt{CATARACT}_2$ dataset using different strategies, we extracted features from the model's final layer. These features were subsequently analyzed with PCA and visualized in a 2D plot.

As shown in Figure A.1 and A.2 in Appendix, projection tuning demonstrated clear class separation using both 1% and 10% of the $\texttt{CATARACT}_2$ dataset for fine-tuning. While last-layer tuning also produced robust results with both 1% and 10%, the model displayed more dispersion and overlap between classes during testing compared to projection tuning. This likely contributed to the observed decline in performance. Additionally, fine-tuning all layers with 10% of the $\texttt{CATARACT}_2$ dataset failed to achieve clear class separation, and with just 1% of the $\texttt{CATARACT}_2$ dataset, the model exhibited almost no discernible decision boundary. Although the rank order of LoRA had little impact on differentiating the decision boundary, it was evident that 1% of the $\texttt{CATARACT}_2$ dataset was inadequate for fine-tuning the pretrained vit-base model, which differed from the results seen with projection tuning. In contrast, 10% data was necessary to detect variations in the feature space.

These findings highlight several advantages of projection tuning for fine-tuning FMs, particularly when dealing with small datasets and near-out-of-distribution scenarios. First, fully fine-tuning FMs demands significant time and resources. For example, as shown in Table 3, fine-tuning all layers of the ViT-base model requires 85.8M parameters, while projection tuning, which focuses on adjusting the linear layer, only fine-tunes 0.59M parameters. Moreover, while full fine-tuning can risk overfitting due to the broader parameter adjustments, projection tuning's focus on the linear layer reduces this risk. Second, unlike last-layer tuning, which adjusts parameters only after the data has passed through the entire architecture, projection tuning modifies the model before it enters the encoder. This approach enhances the model's adaptability and robustness, contributing to improved performance under challenging conditions.

Table 3: Comparison of floating point operations per second (FLOPS) alongside the parameter counts for deep learning models.

Model	GFLOPS	# of Parameters
VGG-11	7.61	128.78M
ResNet-18	1.83	11.2M
MobileNetV2	0.33	2.2M
EfficientNet B0	0.42	4.0M
DeiT-Ti	1.08	5.5M
DeiT-distilled	1.08	5.5M
Mobile ViT-S	1.47	4.9M
EfficientFormer-L1	1.32	11.4M
ViT-base	16.87	85.8M
ViT-base + last layer tuning	16.87	2307
ViT-base + projection tuning	16.87	0.59M
ViT-base + LoRA (rank = 8)	17.67	0.44M

4 Discussion

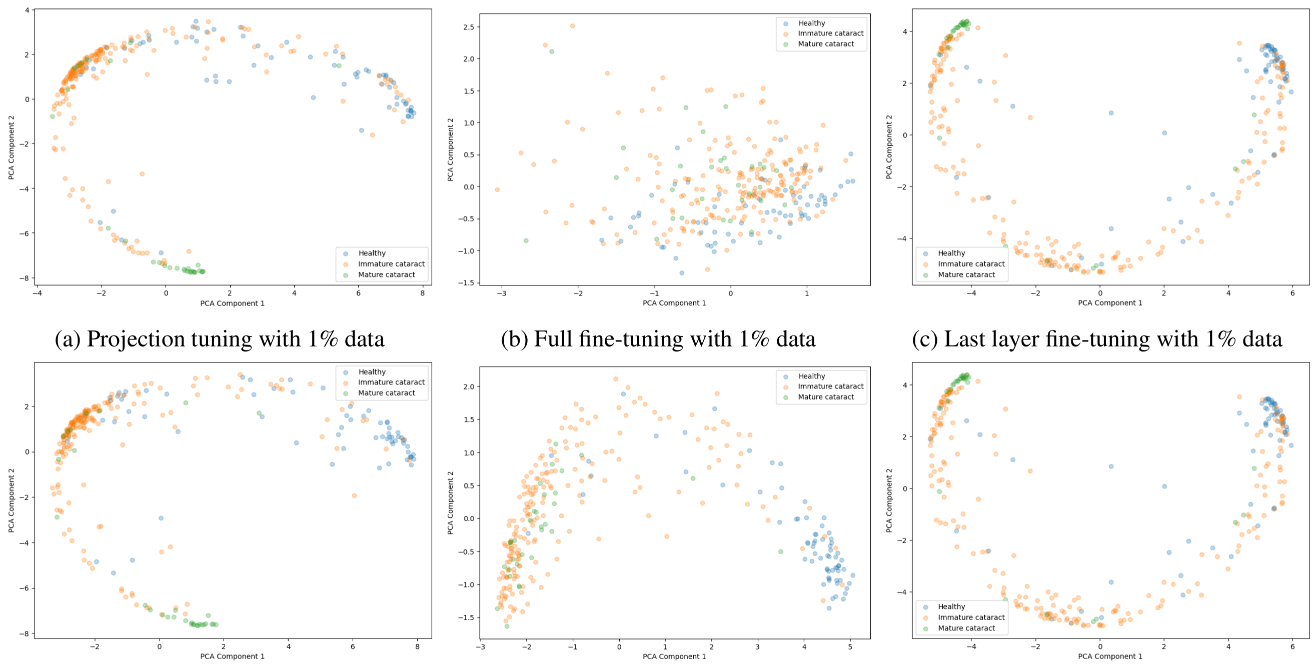
We employed deep learning models with anterior segment eye images captured by a novel smartphone-based diffuse illumination imaging modality to predict lens status in South Indian individuals, beginning with segmentation to eliminate unwanted areas and followed by classification to distinguish between healthy eyes, immature cataracts, and mature cataracts. Our comprehensive evaluation shows that segmentation improves prediction performance, particularly in the context of small datasets. Moreover, we found that projection tuning proved to be an effective fine-tuning strategy, reducing overfitting and improving robustness against data distribution shifts in smaller datasets.

The ViT-base pretrained on $\texttt{CATARACT}_1$ exhibited limited zero-shot performance on $\texttt{CATARACT}_2$, despite having more parameters than other models. This is particularly evident when working with small, real-world datasets like ours, where the benefits of FMs are not fully realized due to the lack of extensive training data. Additionally, FMs in medical imaging face limitations due to incomplete representation of modalities during pretraining, reducing their effectiveness in specialized applications. Our findings suggest that projection tuning is an effective approach for fine-tuning large models on smaller datasets, addressing model capacity with real-world data limitations.

Projection tuning outperformed other fine-tuning methods, such as full-layer and last-layer tuning, especially in near out-of-distribution scenarios with small datasets. Exploring different projection head architectures could further enhance these results. Additionally, comparing projection tuning with other parameter-efficient methods with different vision FMs beyond ViT-base is also necessary to validate its broader applicability.

The ultimate goal of our project is to develop an accurate and efficient cataract detection model for smartphone deployment and broad implementation. Several parameters must be considered to ensure successful deployment on mobile platforms, including model compression to maintain high performance without sacrificing accuracy. Additionally, since our segmentation module required extra annotations for training, it is essential to explore the use of image augmentation as an alternative approach. This could potentially eliminate the need for a separate segmentation step, reduce the associated manual labor, while learning the general representation for inference.

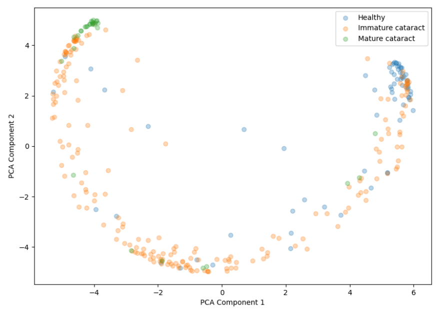
A Appendix



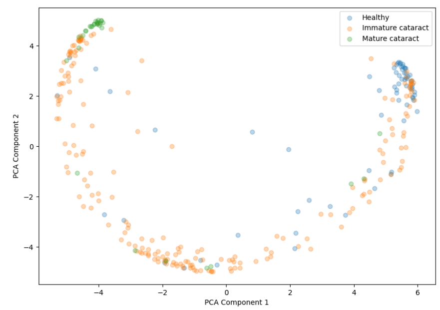
(a) Projection tuning with 1% data (b) Full fine-tuning with 1% data (c) Last layer fine-tuning with 1% data

(d) Projection tuning with 10% data (e) Full fine-tuning with 10% data (f) Last layer fine-tuning with 10% data

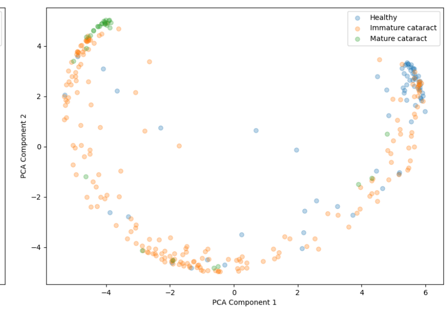
Figure A.1: 2D PCA plots comparing projection tuning, full fine-tuning, and last layer fine-tuning strategies across different dataset sizes.



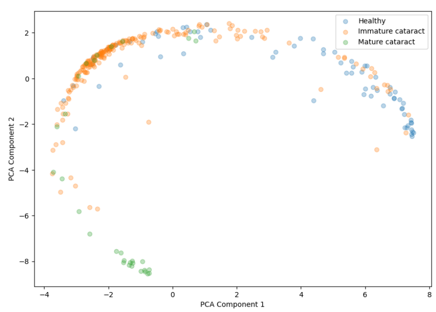
(a) LoRA with 1% data (rank = 2)



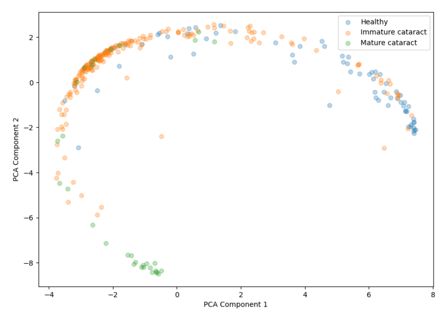
(b) LoRA with 1% data (rank = 4)



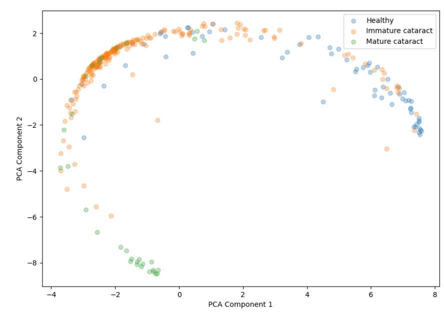
(c) LoRA with 1% data (rank = 8)



(d) LoRA with 10% data (rank = 2)



(e) LoRA with 10% data (rank = 4)



(f) LoRA with 10% data (rank = 8)

Figure A.2: 2D PCA plots showing LoRA fine-tuning across different dataset sizes and ranks.

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