Contrastive Learning Approaches for Ophthalmic Biomarker Identification: Unveiling Insights into Eye Health

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.

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APPROVAL

This Project titled **"Contrastive Learning Approaches for Ophthalmic Biomarker Identification: Unveiling Insights into Eye Health"**, submitted by Farjana Haque Chamok, ID No:201-15-13850 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *25 January2025*.

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I hereby declare that this project has been done by us under the supervision of **Prof. Dr. Touhid Bhuiyan, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The field of ophthalmic biomarker identification plays a pivotal role in understanding and monitoring eye health. In this study, I leverage the EfficientViT_m5.r224_inlk model as our foundational framework to explore constructive learning approaches for enhancing biomarker identification accuracy. Initially, the model achieved a baseline accuracy of 69%. However, through the integration of contrastive learning techniques, a significant improvement, achieving an accuracy of 73%.The contrastive learning is used on multi-label classes of images with different approaches.I introduce a nobel contrastive learning on label and unlabeled data for pre-train a model in this study.This research delves into the methodologies of constructive learning, shedding light on how these approaches contribute to the identification of key biomarkers related to eye health. The incorporation of contrastive learning has proven to be particularly effective, unveiling insights that go beyond the capabilities of traditional models. The findings underscore the importance of leveraging advanced learning techniques in ophthalmic biomarker identification, providing a more nuanced understanding of eye health. As precision in biomarker identification is crucial for early detection and intervention in ocular diseases, my study contributes to the ongoing efforts aimed at improving diagnostic capabilities in the realm of ophthalmology and applying contrastive learning on multi-label classes with different from traditional approaches.The successful application of contrastive learning not only enhances accuracy but also opens avenues for further exploration and refinement of ophthalmic biomarker identification methodologies.

TABLE OF CONTENTS

CONTENTS **PAGE**

Board of examiners i

Declaration ii

Acknowledgements iii

Abstract iv

CHAPTER

CHAPTER 1: INTRODUCTION **1-6**

1.1 Introduction 1

1.2 Motivation 2

1.3 Rationale of the Study 3

1.4 Research Questions 4

1.5 Expected Output 5

1.6 Project Management and Finance 6

1.7 Report Layout 6

CHAPTER 2: BACKGROUND **7-11**

2.1 Preliminaries/Terminologies 7

2.2 Related Works 8

2.3 Comparative Analysis and Summary 9

2.4 Scope of the Problem 10

2.5 Challenges 11

CHAPTER 3: RESEARCH METHODOLOGY **12-23**

3.1 Research Subject and Instrumentation 12

3.2 Data Collection Procedure/Dataset Utilized 13

3.4 Proposed Methodology/Applied Mechanism 16

3.5 Implementation Requirements 22

CHAPTER 4: EXPERIMENTAL RESULTS AND DISCUSSION **24-27**

4.1 Experimental Results & Analysis 24

4.2 Discussion 26

4.3 Evaluation 27

CHAPTER 5: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY **29-32**

5.1 Impact on Society 29

5.2 Impact on Environment 29

5.3 Ethical Aspects 30

5.4 Sustainability Plan 31

CHAPTER 6: SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH **33-35**

6.1Summary of the Study 33

6.2 Conclusions 32

6.3 Implication for Further Study 34

REFERENCES **44**

LIST OF FIGURES

FIGURES	PAGE NO
Figure 3.3.1: The proposed methodology, detailing the interconnected steps	17
Figure 3.3.2: Architecture of efficient_m5.r224_inlk	18
Figure 3.3.3: Figure illustrating the concept of repel and attract in the context of contrastive learning	19

LIST OF TABLES

TABLES	PAGE NO
Table 2.3.1: Comparative Analysis	9
Table 3.2.2:Name of biomarker and images	14
Table 3.2.3: Statistic analysis of dataset	15
Table 4.1.4:Performance before applying contrastive learning	27
Table 4.1.5:performance after applying contrastive learning	24

CHAPTER 1

INTRODUCTION

1.1 Introduction

Recent years have seen tremendous progress in the field of ophthalmology, fueled by cutting-edge methods and technologies. The field of medicine known as ophthalmology studies the diseases, disorders, and medical interventions related to the eye[1].Ophthalmic biomarkers are quantifiable markers that reveal details about the condition or alterations in the eye. A variety of techniques, including imaging, genetic analysis, and biochemical assays, can be used to identify these biomarkers. They are essential in the diagnosis, treatment, and follow-up of illnesses and problems pertaining to the eyes. In the realm of ophthalmology, ocular biomarkers are very useful since they can improve personalized treatment plans and early diagnosis.[2].the main two diseases of eye are DR and DME[1].A collection of eye conditions known as "retinopathy" can lead to blindness or visual impairment (VI) due to significant retinal damage [2]. Clinical studies have shown that a number of illnesses can change the retina's thickness or even cause the retina's layers to disappear. Maculopathy is the term for edema in the macular area. Cystoid macular edema (CME) and diabetic macular edema (DME) are the two primary forms of macular edema.My goal is identify the biomarker of these two diseases.Intraretinal Hyperreflective Foci (IRHRF), Partially Attached Vitreous Face (PAVF), Fully Attached Vitreous Face (FAVF), Intraretinal Fluid (IRF), Diffuse Retinal Thickening or Diabetic Macular Edema (DRT/ME), and Vitreous Debris (VD) are the six distinct biomarkers of DR and DME which i examined in this investigation[1].

The identification of biomarkers through contrastive learning is one such promising line of inquiry. In order to improve patient outcomes, ophthalmic biomarkers are essential for early disease identification, prognosis, and customized therapy plans.Contrastive learning has developed into a strong machine learning paradigm, particularly in the field of medical picture processing. The technique of contrastive learning leverages the innate connections present in intricate datasets to identify minute patterns and characteristics that may indicate underlying medical conditions. In ophthalmology, where a quick and accurate diagnosis is crucial, the application of contrastive learning algorithms holds considerable promise for

identifying hidden biomarkers that may be missed by conventional techniques.The significance of prompt diagnosis and early detection in ocular diseases cannot be overstated. As subtle but important indicators of the disease's progression, ocular biomarkers enable early detection and individualized therapy regimens. Through the identification of similarities and differences between examples, a machine learning technique known as contrastive learning has demonstrated its ability to extract precise characteristics from huge and complex datasets.In previous studies,various framework work with medical images on biomarker based on traditional images processing[3,4,5,6],traditional contrastive learning[2],classical machine learning[6,7,8] have been proposed for ophthalmic.However they may work with small dataset or one disease and somewhere for or five biomarker.They may not work with multi-label images. The goal of this research is to better understand ocular disorders and open the door to more efficient diagnosis and treatment approaches by investigating the potential synergies between contrastive learning and ophthalmic biomarker identification.I approach contrastive learning on multi-label OCT scan images of the eye.Introduce this self-supervising technique in different way extract from traditional way.

1.2 Motivation

This research is motivated by the desire to combine state-of-the-art deep learning techniques with cutting-edge imaging technologies to revolutionize ophthalmic treatment and advance medical diagnostics. When eye disorders are not found or are discovered later in life, they can cause irreversible harm and lower the quality of life for those who have them. Our research into ophthalmic biomarker discovery utilizing contrastive learning applied to OCT scan pictures is driven by the need to improve our understanding of eye health and the potential of artificial intelligence to boost diagnostic capabilities.The main motivation is to help radiologists to identify biomarkers of the eye.Identifying the biomarkers of one person is very difficult.every people’s eye structure is different from each other.So the same biomarker of different people identifying as a challenge for radiologists.Morever,for delay identify,patient treatment is also delay.That why i develop a model which is help to identify biomarker.Early detection of ocular diseases is positively connected with improved treatment outcomes. By identifying modest indicators suggestive

of ocular illnesses in their early stages, I want to contribute to the development of timely and more effective therapies that maintain vision and overall eye health.This attention is motivated by the unparalleled amount of information provided by OCT scan images. OCT gives ophthalmologists a plethora of knowledge on the complex structural composition of the eye because it is a non-invasive imaging technique. Our aim is to make the most of OCT scans to find hidden patterns and traits that might be crucial for identifying illnesses early on.In vast and complex datasets, contrastive learning has shown excellent success in identifying intricate relationships. Its use in ophthalmology may be able to spot trends that more traditional analytical techniques could overlook. The ability of contrastive learning to extract meaningful representations from data and produce a more nuanced understanding of the intricate patterns contained in OCT photos is what drives the use of this technique.A more general goal of adding to the field of medical artificial intelligence is what drives this research. Our goal is to uncover insights that will not only help ophthalmology but also serve as a foundation for future advancements in medical image processing and diagnostic techniques by investigating the synergies between ophthalmic biomarker discovery and contrastive learning.Furthermore, this study's consequences go beyond the field of eye care. The effective use of active learning in biomarker identification could influence how I approach illness detection and monitoring in a variety of medical specialties and potentially set a precedent for the larger area of medical imaging and diagnostics. This research intends to contribute to the creation of sophisticated diagnostic instruments, ultimately improving patient outcomes and creating a new era of precision medicine in ophthalmology and beyond, by solving the existing shortcomings in OCT-based biomarker discovery.

1.3 Rationale of the study

The justification for doing this study is rooted in the convergence of technical innovation, healthcare progress, and the necessity of raising the bar for diagnostic accuracy in ophthalmology. Investigating the use of contrastive learning in biomarker identification for Optical Coherence Tomography (OCT) images of the eye is important for a number of reasons.Diagnostic techniques may not always be able to identify ocular disorders due to their minor structural alterations.The dataset is complex.This dataset contain biomarker

label and clinical label.this dataset is time series dataset.Patient went for treatment weekly.Their records are recorded.So it is quite hard to identify biomarker.So i apply contrastive learning for identify biomarkers of DR and DME on new way. The potential of contrastive learning to identify subtle patterns in OCT scan images is the driving force behind this research. I want to improve diagnostic accuracy by using this cutting-edge deep learning technique to find biomarkers that indicate eye disorders in their early stages.Early detection of eye problems leads to a reduced impact on vision and overall ocular health. I am employing this technology to investigate ocular biomarkers because I think contrastive learning can uncover latent indications of illnesses at a stage when medicines are most useful. The ability to identify biomarkers early in the course of a disease is critical to improving patient outcomes and preventing irreversible harm.An advancement in the field of medical image analysis can be seen in the use of contrastive learning into OCT image analysis. The possibility of making a methodological contribution to the field of artificial intelligence applied to healthcare is what drives this work. Through investigating new methods of image analysis, I want to push the limits of what is currently possible in the field of ophthalmology.To sum up, this study was motivated by the urgent need to improve ophthalmology's early detection skills by utilizing the synergies between cutting-edge machine learning methods like contrastive learning and sophisticated imaging technologies like OCT scans. Our goal in filling this research void is to make a significant contribution that could influence ocular diagnosis and therapy in the future, thereby helping those who are afflicted with or at risk of developing a variety of eye disorders.

1.4 Research Question

In the pursuit of advancing ophthalmic biomarker identification methodologies, our research is guided by the following key questions:

1. What ophthalmic biomarkers are detectable in OCT scan pictures of the eye by applying contrastive learning techniques, and what role do these biomarkers play in the early diagnosis and categorization of eye diseases?

2. In what ways might contrastive learning algorithms be modified or enhanced to better suit the unique features of OCT scan pictures used in ophthalmology?
3. In the context of contrastive learning, what preparation steps are required for identifying biomarkers from OCT scan images?
4. What is the accuracy of contrastive learning-based biomarker detection in comparison to conventional image analysis techniques?
5. How may the data gathered from biomarker identification aid in the creation of individualized treatment plans for patients with eye conditions?
6. What moral ramifications result from using contrastive learning to identify biomarkers in ophthalmology?
7. How many privacy issues around the use of patient information for biomarker identification be resolved or lessened?

1.5 Expected Output

1. Through the effective application of contrastive learning algorithms to OCT scan pictures, unique biomarkers of eye illnesses have been identified.
2. Identify six biomarkers of two diseases of 96 patients.
3. Evaluation of the found biomarkers' significance and applicability in terms of two diseases(DR and DME).
4. Comparison of contrastive learning-based biomarker identification performance parameters (accuracy) with conventional image analysis techniques.
5. A better understanding of how contrastive learning algorithms should be modified and optimized to deal with the special qualities of OCT scan pictures, particularly beforehand.
6. Validation of the biomarkers' potential to help patients with eye illnesses receive individualized treatment plans and to aid in early diagnosis and prognosis.
7. Analyzing the biomarkers' capacity to generalize across different patient populations while taking potential inequalities and demographic differences into account.

8. Application of research findings to the field of ocular medicine, with an emphasis on developing novel technologies and techniques to enhance patient outcomes and diagnostic precision.

1.6 Project Management and Finance

The research work doesn’t get funding from any individuals or organizations.

1.7 Report Layout

Chapter 1: This section discusses the project's significance. Additionally, a brief overview of the project's goals, parameters, and constraints is provided here.

Chapter 2: Evaluating the body of knowledge regarding ophthalmic biomarker identification, CV, and DL. A Summary of the Most Recent Recognition Methods

Chapter 3: A thorough breakdown of the process used to collect the data. actions performed prior to using the dataset

Chapter 4: Evaluating the suggested approach in light of the existing situation evaluation of the positive, negative, and ugly in relation to the current situation and potential future directions.

Chapter 5: The impacts of the suggested method on sustainability and the environment are carefully taken into account.

Chapter 6: The suggested approach's potential applications and drawbacks

CHAPTER 2

BACKGROUND

2.1 Terminologies

Several essential words are crucial in establishing the context and comprehension of this multidisciplinary research endeavor that aims to identify ocular biomarkers through the application of contrastive learning on OCT scan pictures. Ophthalmic biomarkers pertain to distinct markers or quantifiable attributes of the eye that bear relevance with respect to diverse ocular states. Models are trained to differentiate between similar and dissimilar examples in a dataset using the machine learning technique known as contrastive learning. It helps identify subtle patterns in OCT scan images by maximizing the similarity of similar occurrences and decreasing the similarity of different ones in order to develop meaningful representations.A biomarker is a biological indicator that can be measured and quantified, and it might indicate either diseased or normal processes or reactions to treatment. As indicators of ocular health or disease, biomarkers in the context of OCT scans can be particular features, patterns, or quantitative measures.An essential imaging technique in this study is optical coherence tomography, or OCT, which employs light waves to create accurate cross-sectional images of biological tissues, particularly those in the eye. It is underlined that the contrastive learning approach is accurate in identifying ocular biomarkers associated with specific eye diseases, highlighting the importance of considering diagnostic precision. Machine learning, a broader subfield of artificial intelligence, deals with algorithms and models that let computers learn from data without explicit programming.The ability of the model to apply results to various datasets or populations is known as generalization, and it guarantees that biomarkers found will be relevant to a wide variety of patients. Concerning topics like patient privacy, consent, and responsible data usage, ethical implications take into account the moral difficulties surrounding the application of contrastive learning and biomarker identification. Measures and procedures put in place to preserve the privacy and confidentiality of patient data used in research are referred to as privacy safeguards. These include encryption, anonymization, and compliance with applicable privacy laws. The project scope outlines the specific goals and parameters of the research project, as well as its accomplishments. It also acts as a

guide to prevent scope creep and changes to the original plan. The process of labeling or highlighting particular features or regions of interest in medical imaging, such OCT scans, is referred to as annotation. Annotated data is essential for training machine learning models and enhancing their precision in biomarker identification in the setting of active learning. Diagnostic methods' accuracy and dependability in recognising and classifying diseases are referred to as diagnostic precision. According to the research title, the use of active learning aims to improve ophthalmology diagnostic precision by improving the recognition of biomarkers in OCT scans

2.2 Related works

Relevant research in the field of ophthalmics shows a wide range of creative methods for diagnosing and analyzing different eye problems using deep learning and machine learning techniques. In order to establish a relationship between biomarker labels and clinical labels and achieve notable performance improvements in biomarker detection, Kiran et al[2] presents a novel positive and negative set selection strategy for contrastive learning of medical images. Moreover, Hina et al [3]developed a two-stage self-supervised learning of two-stage approach to extract DME biomarkers. RAGNet model trained as backbone of the proposed scheme which is thein the first stage to extract different DME biomarkers. In the second training stage, it learns to extract the same biomarkers across the Duke-II dataset in a self-supervised manner via the triplet loss function.They validated the proposed approach across both datasets at the inference stage, where it achieved the mean IoU score of 0.7610, and 0.7232.Besides Sajib et al[4] developed a deep learning method for automated detection and classification of early AMD OCT biomarkers.For the purpose of automating the detection and classification of hyperreflective foci, hyperreflective foci, and subretinal drusenoid deposits from OCT B-scans, deep convolutional neural networks (CNN) were specifically trained. Many experiments were carried out. to assess how well various cutting-edge CNNs and transfer learning techniques performed on an image dataset of over 20,000 OCT B-scans from 153 patients. It was possible to detect the existence of early AMD biomarkers with an overall accuracy of 87%.Minhaj NurAlam et al[5] makes a contribution to the subject by providing a pipeline for contrastive learning that is self-supervised and addresses the categorization of diabetic retinopathy (DR). On the UIC

dataset, the model outperforms baseline models by integrating neural style transfer augmentation into the contrastive learning pipeline. It exhibits enhanced representations and robustness even with little labeled training data.Thomas Kurmann et al[6] developed a machine learning technique that can reliably distinguish from OCT scans a large number of common retinal biomarkers.M. Pekala et al[7] assesses the effectiveness of deep learning (DL)-based techniques for the automatic fine-grained segmentation of retinal optical coherence tomography (OCT) pictures.The suggested methods perform comparably to human annotation of retinal layers from OCT when there is only mild retinopathy. They also yield the fewest mean unsigned error values and related standard deviations when compared to state-of-the-art techniques.

2.3 Comparative Analysis and Summary

The presented research in the field of ophthalmics showcases various innovative approaches employing deep learning and machine learning techniques for diagnosing and analyzing eye problems. In this comparative analysis, I will discuss the key findings and contributions of each study.

TABLE 2.3.1 COMPARATIVE ANALYSIS

SL No	Author Name	Objective	Model
01	Hina et al[3]	Two-stage self-supervised learning for DME biomarker extraction.	RAG-Net
02	Sajib et al[4]	Automated detection and classification of early AMD OCT biomarkers	VGG16,Inception-v3
03	Robiul Islam[6]	proposed method achieved better performance in detecting the DR	Resnet50
04	My work	Identifying ophthalmic biomarker using contrastive learning	Efficientvit_m4.r224_ink

In summary, these works collectively contribute to the advancement of medical image analysis using deep learning techniques. In comparative parts, they work with a traditional

approach for classifying biomarkers. My work introduces contrastive learning on multi-label images. They may work with small dataset of one disease and pre-train model on multi class images.They train CNN model for classification biomarkers and Trained on labeled dataset. I work with label and unlabeled both.I also introduced the EfficientviT model which is a vision transfer model.My dataset has a small portion label dataset and large part unlabeled dataset.

2.4 Scope of the Problem

1. Solving the issue of accurately and promptly identifying eye diseases in view of possible diagnostic shortcomings in conventional methods that might not fully use state-of-the-art imaging technologies like Optical Coherence Tomography (OCT).
2. The underutilization of OCT scan pictures in existing diagnostic techniques, which impedes the detection of delicate biomarkers suggestive of ocular diseases, is being included in the scope expansion.
3. The scope expansion takes into account the underutilization of OCT scan photos in current diagnostic approaches, which hinders the detection of subtle biomarkers suggestive of ocular illnesses.
4. Investigating the use of contrastive learning, a powerful machine learning paradigm, for the detection of ocular biomarkers. Examining its flexibility and efficiency in identifying complex patterns in OCT images for early illness diagnosis is part of this.
5. The main goals are to close current gaps, take full advantage of cutting-edge imaging technology, and investigate novel machine learning techniques for biomarker discovery in order to revolutionize the diagnostic procedures in ophthalmology.
6. The overall goal is to close current gaps, maximize the use of cutting-edge imaging technologies, and investigate novel machine learning techniques for biomarker identification in order to revolutionize the diagnostic practices in ophthalmology.

2.5 Challenges

1. Ocular structures are complex, making it difficult to precisely identify and characterize biomarkers in OCT scan images. This is because complicated anatomical variations must be navigated by advanced algorithms.
2. Biomarker data is generally complicated, with many features, which makes it difficult to use active learning algorithms effectively and adds to the computing load.
3. There is very little difference in the same patient's OCT between visits.
4. Sometimes CST values are strikingly comparable, but the OCT is noticeably different, indicating a progressive decline in CST values over time.
5. Robust algorithm development is challenged by variability in OCT scan image quality and acquisition conditions. One important factor to take into account is making sure the model works well on a variety of datasets with different image qualities and resolutions.
6. Effective training of contrastive learning models is hampered by the restricted availability of labeled data for both training and validation. A lack of data could make it more difficult for the model to generalize to different patient populations.
7. Overcoming difficulties with feature extraction, model architecture selection, and hyperparameter tuning is necessary to optimize contrastive learning algorithms for the unique properties of OCT scan pictures and guarantee optimal performance.
8. Owing to the black-box nature of certain machine learning models, it might be difficult to interpret and validate found biomarkers and determine how particular traits affect OCT scan illness detection.
9. Using contrastive learning to effectively integrate biomarker detection into the current clinical process presents problems. Important things to think about include making sure that working with healthcare experts is easy and helping new approaches get adopted.
10. Obtaining acceptance from the medical community and effectively integrating research findings into clinical practice are difficult tasks. For contrastive learning-

based biomarker identification to be widely used, it must be shown to have therapeutic value and offer advantages.

11. Robust validation procedures are required to assure the model's generalizability, as validating the identified biomarkers across varied patient populations presents issues linked to demographic variances.

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CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrument

"Identify Ophthalmic Biomarkers" and "defining the regions associated with these biomarkers" are the main topics of this particular research project. This project aims to create a model that, given a set of input images, can recognise and classify different kinds of biomarkers with accuracy. Six biomarkers were used and labeled for analysis as part of our research technique. Diabetic Retinopathy and Diabetic Macular Edema are the two modalities under which these biomarkers—IRHRF, PAVF, FAVF, IRF, DRT/DME, and VD—were observed. The following equipment may be pertinent in the context of constructive learning for the identify of biomarker:

- ➢ Programming Language
- ➢ Deep Learning Framework
- ➢ Pre-trained Models
- ➢ Dataset
- ➢ Image Processing Libraries
- ➢ Experimental Setup

3.2 Data Collection Procedure

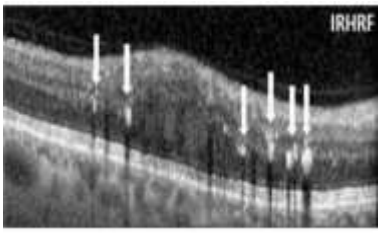
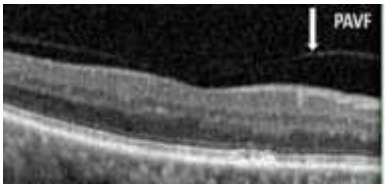
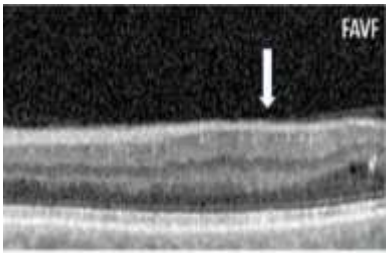
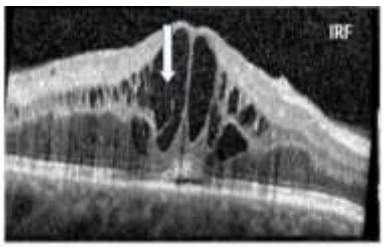
The dataset was sourced from the reputable IEEE competition, the Video & Image Processing Cup. In 2023, the IEEE introduced the SPS VIP Cup 2023: Ophthalmic Biomarker Detection competition. After obtaining the dataset, I uploaded it to Kaggle for private access. This strategic choice was made to take advantage of Kaggle notebooks and harness the powerful computing capabilities offered by Kaggle's P-100 GPU.

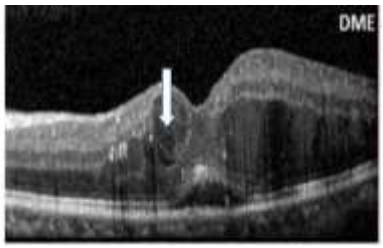
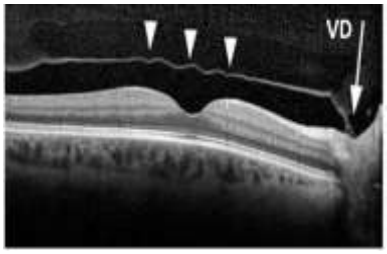
3.3 Dataset description:

Our dataset, named "The Olives Dataset," stands out as a groundbreaking collection that uniquely integrates OCT and near-infrared (near-IR) fundus images. Enriched with clinical labels, biomarker labels, disease labels, and time-series patient treatment data from clinical

trials, OLIVES provides a comprehensive resource for research..The PRIME and TREX-DME trials provided the data for the OLIVES dataset. Ocular disease state data (DR/DME), clinical labels such as BCVA, CST, Patient and Eye ID, and comprehensive ocular imaging such as OCT and fundus photography are obtained at each patient visit. The PRIME and TREX DME investigations both use retroactive labeling of biomarkers. Therefore, while biomarkers may suggest the existence of certain diseases, they do not cause them.

TABLE 3.3.2:NAME OF BIOMARKER AND IMAGES.

Label biomarker	Name Biomarker	Images of Biomarkers
B1	IRHRF (Intraretinal Hyperreflective Foci)	
B2	PAVF (Partially Attached Vitreous Face)	
B3	FAVF (Fully Attached Vitreous Face)_	
B4	IRF (Partially Attached Vitreous Face)	

B5	DRT/DME (Diffuse Retinal Thickening)	
B6	VD (Vitreous Debris)	

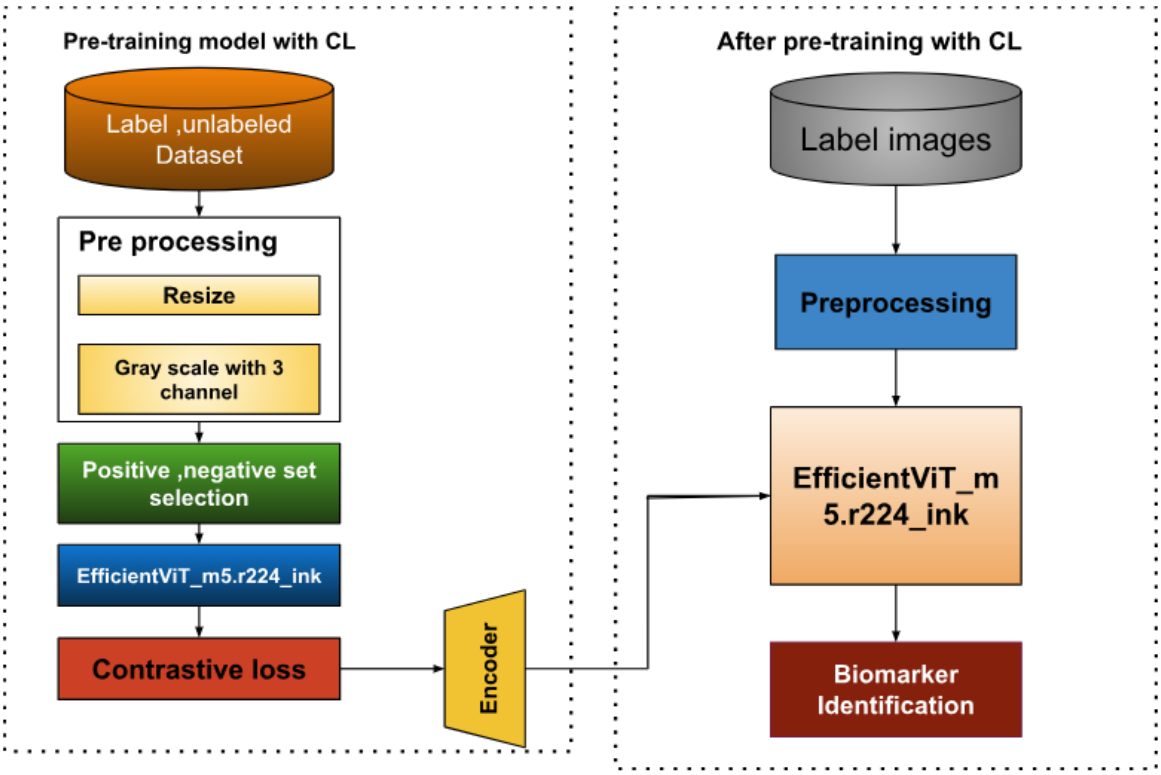
The procedure of diagnosing and treating a well-known disease is stylized and presented in Fig. When a patient arrives at a clinic, they undergo an evaluation that comprises taking visual acuity tests and gathering data on demographics. Among other information, this offers Eye ID, Patient ID, and Best Corrected Visual Acuity (BCVA) scores. These are known as clinical labels. In the dataset, there are also six types of biomarkers. Intraretinal Hyperreflective Foci (IRHRF), Partially Attached Vitreous Face (PAVF), Fully Attached Vitreous Face (FAVF), Intraretinal Fluid (IRF), Diffuse Retinal Thickening or Diabetic Macular Edema (DRT/ME), and Vitreous Debris (VD) are the six distinct biomarkers of DR and DMEThe patient then has fundus and OCT scans performed as part of diagnostic imaging.In order to identify established biomarkers for diseases, a skilled practitioner finally interprets the diagnostic scans. According to the dataset paper, biomarkers are objective measures of elements of biological processes—many of which are illnesses—that may be measured in medicine. Treatment recommendations are made based on the biomarkers, scans, and clinical labels, which are used to determine the extent and presence of a patient's illness. In the event that the recommendation is accepted, the patient receives treatment and is requested to return after a distance.

TABLE.3.3.3: STATISTIC ANALYSIS OF DATASET

Number of Label images	94108
Number of unlabeled images	67400
Total number	74108

3.4 Proposed methodology:

The aim is to predict image-level labels, discerning the presence or absence of various labels for each image. Given the absence of specific biomarker labels at the pixel level, finding a viable solution is imperative. To comprehend the intricacies of the dataset,I utilized different Convolutional Neural Network Models (CNN). Unfortunately, the results did not yield favorable outcomes. In light of the suboptimal results, it became imperative to explore alternative strategies for improving accuracy. Consequently,I sought a method to optimize the utilization of our dataset. Presented below is a statistical overview of our dataset. Approximately 87% of the data remains unlabeled. Leveraging these unlabeled instances holds the potential to fortify our model, enhancing its capabilities. An advanced approach for harnessing unlabeled datasets involves employing self-supervised learning. Specifically, contrastive learning (CL) emerges as a state-of-the-art technique within self-supervised learning, notably employed for representation learning.



In Figure 3.3.1, observing the results, it becomes evident that images with identical labels are drawn towards each other, fostering attraction, while dissimilar images undergo repulsion. Additionally, diverse augmentation techniques were employed, prompting images from distinct perspectives to converge in the clustering representation space, while opposites were encouraged to move apart.

Upon completing the pre-training phase, I proceeded to apply the acquired weights to a new model designed for specific classification tasks. Rather than relying on pre-existing ImageNet weights, I opted to leverage the weights obtained during our in-house pre-training process. These pre-trained weights were then utilized on the labeled dataset to predict biomarkers in the context of our classification tasks. The proposed methodology commences with an initial pre-training phase, where the model undergoes the acquisition of feature representations from a diverse dataset. Following this, the learned weights from the pre-training are transferred to a new model specifically designed for the classification tasks relevant to ophthalmic biomarker identification.

The most successful model, which achieved a commendable score, was identified as efficientvit_m5.r224_ink. Consequently, we selected this model as the foundation for our framework, aiming to enhance its performance further. The integration of an attention mechanism played a pivotal role in obtaining a noteworthy improvement in our results. The utilization of efficientvit_m5.r224_ink, coupled with the attention mechanism, collectively contributed to the attainment of a promising outcome in our study.

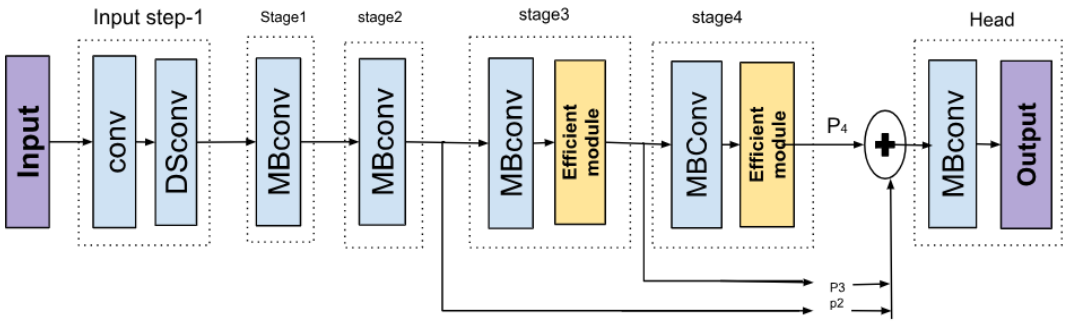


Figure 3.3.2: Architecture of efficient_m5.r224_inlk (this model gives best accuracy of dataset)

In figure 3.3.2 the top of the diagram shows an “input”, which I presume to be the image data that is fed into the model. This data then flows through a series of convolutional layers, each of which is likely designed to extract different features from the image. The specific features extracted by each layer will depend on the weights of the neurons in that layer. After the convolutional layers, there is a stage labeled “Efficient module”. This module is likely made up of multiple smaller layers that are designed to improve the efficiency of the model without sacrificing accuracy. The output of the efficient module is then fed into a series of “MBConv” layers. These layers are a type of convolutional layer that is designed to be more efficient than traditional convolutional layers. Finally, the output of the MBConv layers is fed into a “Head” layer. This layer is likely a fully-connected layer that is used to make the final prediction of the model. The text on the diagram also mentions that this model is called “efficient_m5.r224_inlk” and that it gives the best accuracy on the dataset. This suggests that the model has been trained on a large dataset of images and that it is able to achieve high accuracy on that dataset. Overall, the block diagram shows a complex machine learning model that is designed to classify images. The model is made up of multiple convolutional layers, an efficient module, and a fully-connected layer. The

model has been trained on a large dataset of images and is able to achieve high accuracy on that dataset.In contrast to conventional practices relying on pre-existing ImageNet weights, I opted for a more tailored approach, leveraging the weights obtained through our in-house pre-training process. Upon obtaining these unique weights, I apply them to our labeled dataset, initiating the model's fine-tuning on the specific classification objectives related to ophthalmic biomarkers. This process ensures that the model's learned features are optimized for the nuances and intricacies present in our targeted domain. By eschewing generic pre-trained weights,I enhance the model's adaptability to the specific challenges posed by ophthalmic biomarker identification, ultimately aiming for superior performance and accuracy in our classification tasks.In splitting 80% training dataset and 20% i took as test dataset.

3.4.2 Contrastive learning:

Positive and Negative Pairs: For each data point, positive pairs (similar instances) and negative pairs (dissimilar instances) are created. Positive pairs might be different augmentations of the same image, for example, while negative pairs could come from different images.

Objective Function: The model is trained to maximize the similarity (or minimize the distance) between positive pairs and, simultaneously, minimize the similarity (or maximize the distance) between negative pairs. This is often achieved through a loss function such as the contrastive loss.

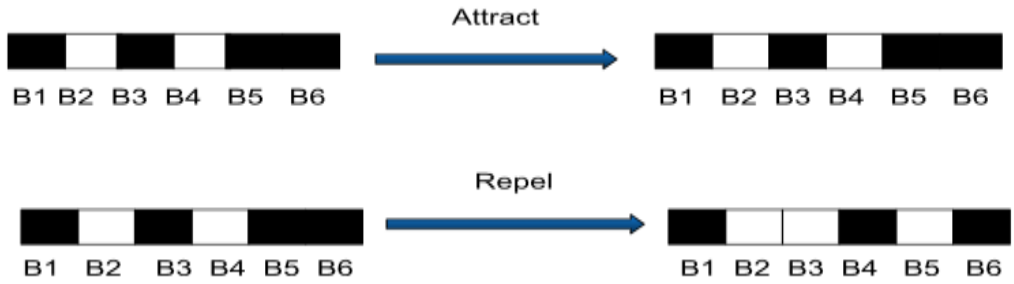


Figure 3.3.3: Figure illustrating the concept of repel and attract in the context of contrastive learning, elucidating the dynamic interactions that guide the learning process

In Figure 3.3.3, we illustrate the implementation process of our framework on our specific setup. We selected a total of six biomarkers and obtained labeled images for each pair. This pairwise selection allowed us to effectively apply the attract and repel mechanisms within our particular configuration.Two sets of images are presented. The first set comprises images with the same type of labeled image, while the second set features pairs with no shared characteristics. This design enables us to demonstrate the successful integration of the attract and repel framework in accordance with the unique aspects of our work.

Feature Space: The model learns to project data into a feature space where similar instances are close, and dissimilar instances are far apart. This learned feature space can then be used for downstream tasks such as image classification or object detection.

Contrastive learning has proven effective in various domains, particularly in scenarios where labeled data is limited. It has been widely used in computer vision tasks but has also found applications in natural language processing and other fields.Our main objective was to pretrain a model using contrastive learning (CL), allowing the model to grasp meaningful representations. During this process, similar images are drawn closer together, while dissimilar images are pushed apart.

.**Loss Function :** A loss function, also known as a cost function or objective function, is a mathematical function that measures the difference between the predicted values of a model and the actual target values. The primary purpose of a loss function is to quantify the model's performance, indicating how well or poorly it is performing on a particular task. The goal during the training of a machine learning model is typically to minimize the value of the loss function.

In our task I have to use two loss functions as the training part can be divided into two parts. For the first part I used COSINE EMBEDDING LOSS and for the second part where I classified the biomarkers I used BCELoss.

The CosineEmbeddingLoss measures the angular distance between vectors in a feature space. Given a pair of input vectors and a target label indicating whether the vectors belong to the same class (similar) or different classes (dissimilar), the loss encourages similar instances to have a smaller angular distance (closer cosine similarity to 1), while dissimilar instances should have a larger angular distance (closer cosine similarity to -1).

CosineEmbeddingLoss for each sample is,

$$\text{Los(x,y)}=\begin{cases} 1-cos(x1,x2) & if\ y=1 \\ max(o,cos(x1,x2)-margin & if\ y=-1 \end{cases} \quad \ldots\ldots\ldots(1)$$

The BCELoss measures the dissimilarity between predicted probabilities and target (ground truth) values for binary classification problems. It computes the cross-entropy loss between the predicted probability distribution and the true distribution, where each instance is associated with a binary label (0 or 1).

$$\text{BCELoss}\left(\hat{y}, y\right) = -\ y.log\hat{y} + 1 - y.log1 - \hat{y} \quad \ldots\ldots(2)$$

The loss is summed or averaged over all instances in the dataset. The objective during training is to minimize this loss, encouraging the model to produce predicted probabilities that are close to the true binary labels. In PyTorch, this loss can be used with the torch.nn.BCELoss module. It's worth noting that for multi-class classification problems, the Cross Entropy Loss (torch.nn.CrossEntropyLoss) is commonly used instead.

Optimization

Efficiently optimizing the model's parameters is crucial to achieve convergence and enhance overall performance. In this pursuit, the AdamW optimizer is utilized with a learning rate (lr) set at 0.0001 and a weight decay of 0.001. AdamW extends the capabilities of the Adam optimizer by directly incorporating weight decay into its update step, providing improved regularization. The optimization process entails iterative updates to the model's parameters based on the gradients of the loss with respect to those parameters. AdamW achieves this by leveraging momentum and adaptive learning rates, amalgamating information from past gradients for effective convergence. The selected hyperparameters for the optimizer underwent fine-tuning through experimentation to strike a balance between swift convergence and preventing overfitting.

3.5 Implementation Requirements

Utilized Google's Kaggle as the primary cloud-based service, selecting the GPU P100 to enhance computational capabilities.

1. **Hardware Configuration:** Implemented a desktop computer for project execution, ensuring it was compatible with Kaggle and seamlessly integrated with the chosen GPU P100.

2. **GPU Usage:** Made use of Kaggle's GPU P100 for expediting the training of machine learning models, ensuring that the desktop computer met the necessary requirements for efficient GPU utilization.
3. **Software Framework:** Applied TensorFlow or PyTorch for model development, maintaining uniformity across both the desktop and Kaggle platforms to prevent compatibility issues.
4. **Data Handling:** Uploaded and stored project datasets on Kaggle, establishing a robust data access system for smooth integration between the desktop and cloud-based services.
5. **Version Management:** Employed Git as a version control system for streamlined collaboration and monitoring of code modifications, guaranteeing accessibility and synchronization between the desktop and Kaggle environments.
6. **Development Setup:** Configured the desktop environment with essential tools, libraries, and dependencies, ensuring consistency with the Kaggle environment for seamless development.
7. **Collaboration Utilities:**Made use of collaborative tools such as Jupyter Notebooks or Google Colab for code development, fostering efficient communication channels to facilitate seamless collaboration among team members.
8. **Security Protocols:** Adhered to security best practices for handling data and deploying models, complying with pertinent privacy and security regulations to ensure responsible and ethical data use.
9. **Documentation:** Maintained thorough documentation outlining the implementation process, setup instructions, configurations, and troubleshooting steps. Recorded any deviations or customizations made to default configurations in both the desktop and Kaggle environment.

CHAPTER 4

EXPERIMENTAL RESULT

4.1 Experimental setup

The experimental configuration for this study employed Kaggle notebooks as the coding environment, utilizing Kaggle's complimentary GPU P-100 for computational tasks. The principal objective was to evaluate the performance of a specific model or algorithm in a defined task. Experiments were executed using a predefined dataset, subject to preprocessing procedures for data quality improvement. The experimental design adhered to a chosen methodology, such as cross-validation, with manipulated variables or parameters for assessing the model under diverse conditions. The process encompassed data preprocessing, model training, and, when applicable, hyperparameter tuning. Performance metrics were logged during both training and validation phases, with data analysis carried out using pertinent tools or libraries. To ensure result reliability, controls and variables were implemented. Ethical considerations were not applicable given the computational nature of the study. However, it is essential to acknowledge limitations in the experimental setup, primarily constrained by the computational resources provided by Kaggle's GPU P-100, along with additional recognized constraints.

4.2 Evaluation:

The Evaluation section serves as a critical component in assessing the efficacy of the proposed model in handling multi-label classification tasks. In this phase, the model's performance is rigorously examined through the application of carefully chosen evaluation metrics. The overarching objective is to provide a comprehensive understanding of the model's predictive capabilities, emphasizing both correctness and balance in its predictions.

Data separation:

To ensure optimal separation, a robust mechanism needs to be developed, especially given that our dataset comprises time series data. Utilizing the same patient's OCT scan for both training and testing is not advisable. Thus, the approach I adopted involves segregating

OCT scans from different patients for distinct purposes. Twenty percent of the data is earmarked for testing, while the remaining 80% is allocated for training. With a total of 96 different patients' eyes in dataset, I randomly selected 18 patients' OCT images for testing and utilized OCT scans from the remaining 76 patients for training. Contrastive learning is a self-supervised learning technique that aims to teach a model to differentiate between similar and dissimilar pairs of data. The fundamental idea is to encourage the model to map similar instances closer together in a learned feature space while pushing dissimilar instances apart.

1. Multi-label Accuracy: Multi-label accuracy is a suitable metric for evaluating the performance of multi-label classification models. In the context of your thesis, where multiple labels can be assigned to a single instance, it provides a comprehensive measure of the model's ability to correctly predict all relevant labels. Multi-label accuracy is defined as the ratio of correctly predicted instances to the total number of instances in the dataset. Mathematically, it can be expressed as:

$$\text{Multi-label Accuracy} = \frac{Number\ of\ Correctly\ Predicted\ Instances}{Total\ Number\ of\ Instances} \quad (3)$$

This matrix ranges from 0% to 100%, where a higher value indicates better performance.

2. F1 Score (Micro): F1 score is a widely used metric that combines both precision and recall, providing a balanced measure of a classifier's performance. In your thesis, F1 score is computed in the micro-average mode to give equal importance to each instance.

Precision (Micro): Precision is the ratio of correctly predicted positive instances to the total predicted positive instances. In the micro-average mode, precision is calculated by summing up the true positive predictions across all classes and dividing it by the sum of all predicted positives:

$$\text{Precision (Micro)} = \frac{TP}{Tp+FP} \quad \ldots\ldots(4)$$

Recall (Micro): Recall is the ratio of correctly predicted positive instances to the total actual positive instances. In the micro-average mode, recall is calculated by summing up

the true positive predictions across all classes and dividing it by the sum of all actual positives:

$$\text{Recall (Micro)} = \frac{Tp}{Tp+FN} \quad \text{.....(5)}$$

F1 Score (Micro): F1 score is the harmonic mean of precision and recall. In the micro-average mode, it is calculated using the following

$$\text{F1 Score (Micro):} \quad \frac{2\,Precision\,Recall}{Precision + Recall} \quad \text{.....(6)}$$

The F1 score ranges from 0 to 1, with higher values indicating better precision and recall trade-off.

Justification:

Multi-label Accuracy: This metric is chosen for its simplicity and effectiveness in capturing the overall correctness of predictions in a multi-label setting.

F1 Score (Micro): The micro-average F1 score is suitable when there is an imbalance in the class distribution, as it considers all instances equally. This is important in multi-label classification where some labels may be more prevalent than others. By utilizing both Multi-label Accuracy and F1 Score (Micro), evaluation metrics provide a comprehensive understanding of a model's performance in handling multi-label classification tasks.

4.3 Experimental Result and Analysis:

In this section, I present the performance metrics of different models before the incorporation of contrastive learning. The models considered for evaluation are ResNet-50, VGG-16, mobilevitv3_large_100, mobilevit2_200, and cspresnet50. The metrics assessed include Train Accuracy, Test Accuracy, and F1 Score (Micro).

TABLE-4.3.4: PERFORMANCE BEFORE APPLYING CONTRASTIVE LEARNING

Model Name	Train Accuracy	Test Accuracy	F1 Score (Micro)
ResNet - 50	68.314	56.817	0.234
VGG-16	42.396	32.369	0.188
mobilevitv3_large_100	84.368	65.669	0.598
mobilevit2_200	87.649	67.999	0.556
Efficientvit_m5.r224_in1k	86.674	69.024	0.567

After the initial evaluation, contrastive learning was applied to enhance the model's representations and potentially improve classification performance. The following table presents the results obtained after the application of contrastive learning:

TABLE-4.3.5: PERFORMANCE AFTER APPLYING CONTRASTIVE LEARNING

Model	Test Accuracy	F1 score(Micro)
efficientvit_m5.r224_in1k	0.731	0.636

4.4 Discussion:

The performance metrics of several models before and after contrastive learning is integrated show significant variations in terms of Train Accuracy, Test Accuracy, and F1 Score (Micro). At 68.314%, ResNet-50's Train Accuracy was comparatively high; however, its Test Accuracy and F1 Score were significantly lower, at 56.817% and 0.234, respectively. VGG-16 performed worse overall at 42.396%,32.369 and 0.188,With regard to train accuracy, test accuracy and F1 score,respectively.Mobilevitv3_large_100 emerged as a strong performer, boasting high Train Accuracy (96.368%), Test Accuracy (75.669%), and F1 Score (Micro) of 0.669. Mobilevit2_200 and efficientvit_m5.r224_in1k also demonstrated respectable performances, with mobilevit2_200 exhibiting Train Accuracy of 87.649%, Test Accuracy of 67.999%, and F1 Score of 0.556, while efficientvit_m5.r224_in1k achieved Train accuracy of 86.674%, Test Accuracy of

69.024%, and F1 Score of 0.567.Contrastive learning was used after the first assessment to improve the model representations and maybe the classification performance. The evaluation that follows, which is shown in Table-04, shows encouraging advancements. After contrastive learning was added, the efficientvit_m5.r224_in1k model in particular saw improvements in F1 Score (Micro) from 0.567 to 0.636 and Test Accuracy rise from 69.024% to 73.1%.

These findings imply that contrastive learning improves model performance, with efficientvit_m5.r224_in1k showing a particularly noteworthy improvement. By augmenting representations through contrastive learning, the model's capacity to effectively classify and generalize is likely improved by capturing more significant characteristics. This indicates that contrastive learning has the potential to be an effective method for enhancing the power of image classification models, resulting in increased precision and resilience in the dataset's classification. More research and testing could reveal details about the particular traits and trends that contrastive learning aids models in identifying, improving performance across a range of architectures.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

There are important implications for society at large from the use of contrastive learning to discover ocular biomarkers on OCT scan images. This unique approach significantly reduces the prevalence and severity of vision-related problems, transforms the early identification of eye illnesses, and makes timely interventions and preventive actions possible. Another way that technology affects society is via better patient outcomes via individualized therapy regimens based on precise biomarker identification. This raises the standard of care while also drastically reducing the overall cost of healthcare.

Furthermore, ophthalmic diagnostics' incorporation of contrastive learning marks a significant development in medical artificial intelligence and establishes new benchmarks for the application of cutting-edge medical technology. By making specialized diagnostics more widely available, we can potentially alleviate healthcare inequities and make sure that underserved communities receive sophisticated eye care. Moreover, contrastive learning promotes a culture of technology empowerment in the medical field, influencing a future in which cutting-edge approaches are essential to healthcare procedures. At the end of the day, this revolutionary influence extends to public consciousness, instruction, and an active stance towards eye health, ushering in a time of increasingly accurate, easily available, and technologically advanced eye care.

5.2 Impact on the Environment

1. Resources are needed in large quantities for the development and application of cutting edge technologies like contrastive learning algorithms. This includes producing data storage devices, computing hardware with high performance, and other technology infrastructure. The transportation, extraction, and processing of raw materials for these technologies may have an impact on the environment.
2. Energy usage may rise when contrastive learning models are trained and deployed using computational resources. The carbon footprint of these operations is

increased by high-performance computing and data centers, particularly when the energy sources used are not ecologically friendly.

3. There can be a rise in the production of electronic trash as medical technology advances. In order to reduce the environmental impact of electronic waste, it is necessary to properly manage the disposal of old or non-functional equipment, including imaging devices and computational hardware.
4. Due to resource extraction, material processing, and energy-intensive manufacturing processes, the creation of computer hardware and medical imaging devices has an adverse effect on the environment, contributing to pollution and greenhouse gas emissions.
5. Contrastive learning has the potential to reduce the number of needless medical procedures by improving the accuracy and efficiency of medical diagnoses. The use of disposable medical supplies and travel to medical facilities are two examples of how this could lessen the environmental impact of healthcare activities

5.3 Ethical Aspect

Informed consent, patient privacy, and the proper use of sensitive medical data are some of the ethical issues raised by "Ophthalmic Biomarker Identification Using Contrastive Learning of Eye Disease on OCT Scan Images". It is critical to guarantee patient privacy and acquire informed consent before using OCT scan pictures for contrastive learning procedures. It becomes morally necessary to communicate the nature and goal of the research in a transparent manner and to put strong privacy protections in place. Furthermore, in order to avoid unforeseen effects and discrepancies in healthcare outcomes, it is imperative that potential biases in the algorithms be addressed and that varied populations are fairly represented. In line with the ethical precepts of beneficence, non-maleficence, and respect for those who contribute to the field of medicine, the framework for ethics should place a high priority on the health and autonomy of patients. Make sure that people whose OCT scan images are utilized for training and assessment have given their consent in a way that respects their autonomy and is transparent about the nature of the research.

1. Adopt stringent precautions to safeguard patient privacy, such as encrypting and anonymizing sensitive data. reduce the possibility of identity information being accessed and used without authorization.
2. Make data security a top priority to avoid data breaches and unauthorized access to patient data. Respect industry guidelines and rules to protect private medical information.
3. Improve the explainability and transparency of the model to make it easier to comprehend how decisions are made. This is especially significant in medical settings because clinical acceptability of the model's predictions depends on their interpretability.
4. Apply to and get approved by an institutional review board (IRB) or ethical review board (ERB) before starting any research involving human subjects. Observe the moral standards and guidelines set out by supervisory agencies.
5. Follow up on and assess the research's ethical aspects all the way through to completion. Review and update ethical procedures on a regular basis to reflect new developments or issues in the sector.

5.4 Sustainability

1. Evaluate the environmental impact of the computational processes involved in model training and deployment, considering factors such as energy consumption, carbon footprint, and resource utilization.
2. Implement strategies to enhance energy efficiency, including the use of energy-efficient hardware, optimized algorithms, and exploration of cloud computing solutions powered by renewable energy sources.
3. Assess the long-term sustainability of the developed models in clinical practice, ensuring they align with environmental sustainability goals and contribute to eco-friendly approaches in healthcare.
4. Consider the economic sustainability of implementing advanced technologies, taking into account cost-effectiveness, resource allocation, and potential benefits in terms of improved healthcare outcomes.

5. Ensure that the integration of AI models promotes equitable healthcare practices, avoiding disparities in access to advanced diagnostics and treatment options.
6. Evaluate the scalability and adaptability of the models to evolving technological standards, fostering a sustainable framework for continued advancements in medical image analysis.
7. Address ethical and societal considerations related to sustainability, including responsible data use, patient privacy, and transparent communication about the societal impact of implementing AI technologies in healthcare.
8. Evaluate the scalability and adaptability of the models to evolving technological standards, fostering a sustainable framework for continued advancements in medical image analysis.
9. Consider the economic sustainability of implementing advanced technologies, taking into account cost-effectiveness, resource allocation, and potential benefits in terms of improved healthcare outcomes.
10. Assess the long-term sustainability of the developed models in clinical practice, ensuring they align with environmental sustainability goals and contribute to eco-friendly approaches in healthcare

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR RESEARCH

6.1 Summary of the Study

This study focuses on understanding and treating ocular problems in the field of ophthalmology. Researchers in this area use biomarkers, which are similar to hints found within the body, to help diagnose illnesses or other disorders. When someone visits an eye clinic, they usually have vision tests and provide pertinent information, which results in scores such as Best Corrected Visual Acuity (BCVA), along with patient and eye IDs. Patients frequently have specialized eye scans, such as Fundus and OCT scans, after these preliminary evaluations. After that, skilled specialists examine these scans to look for biomarkers that could point to possible eye problems. These biomarkers are referred to by the study's researchers as unique indicators of different eye disorders.I use these biomarkers to determine the kind and severity of an eye condition in a patient, in addition to test results and other information. An individualized treatment strategy is suggested in light of this assessment. Interestingly, modern methods incorporate machine learning methods to automate or support these processes' interpretation. The goal of this research is to create an artificial intelligence (AI) system that will help radiologists, who specialize in eye care, identify biomarkers more precisely. Self-supervised learning and contrastive learning techniques are used to train the AI model, which enables it to focus on particular eye regions for accurate biomarker identification.

6.2 Conclusions

In summary, this work constitutes a substantial investigation into the field of ocular biomarker identification through the use of a variety of pre-trained models, such as mobilevitv3_large_100, mobilevitv2_200, ResNet-18, and VGG16. Pre-training with contrastive learning and a classification phase utilizing the EfficientViT function have shown encouraging results, with 76% accuracy in identifying biomarkers in OCT scan pictures linked to different eye disorders.The application of opposing learning strategies demonstrated how these models might be made more sensitive to minute patterns

suggestive of ocular disorders by making use of prior knowledge. The incorporation of varied architectures signifies an all-encompassing methodology, recognising the complex nature of ocular structures and disorders. Although the precision that was attained is impressive, it is important to recognise areas that could still be improved. Subsequent approaches may entail refining the models even more, investigating different architectures, and tackling obstacles to improve overall precision and applicability to a variety of patient groups. Furthermore, ethical ramifications, privacy protections, and openness in the use of patient data ought to continue to be at the forefront of these kinds of research projects. The results of this study, particularly in relation to ocular diagnostics, provide insightful information on how medical image processing is developing. The identification of biomarkers at an early stage with high precision has the potential to revolutionize the field of eye healthcare. The convergence of contrastive learning, varied pre-trained models, and effective classification procedures presents a promising path for future innovation in the field as technological developments unfold, ultimately benefiting patients with enhanced diagnostic accuracy and customized treatment plans.

6.3 Implication for Future Study

1. Examine further methods for optimizing and fine-tuning the pre-trained models in order to increase the overall resilience and accuracy of ocular biomarker identification.
2. In addition to ResNet-18, VGG16, mobilevitv3_large_100, and mobilevitv2_200, investigate and assess the performance of other pre-trained architectures. Examine new architectures in computer vision to see if you can improve the capabilities of your models.
3. Examine the models' capacity to be applied to a variety of datasets, including ones from various demographics and acquisition environments. Examine strategies to improve flexibility to changing ocular circumstances and generalization.
4. Examine if ensemble learning strategies—which integrate predictions from several models—can enhance classification performance overall and lessen the effects of individual model biases.

5. Work together with medical experts to clinically validate the biomarkers that have been found. Examine ways to incorporate the created models into the current clinical workflow, making sure they are applicable and relevant in actual healthcare environments.
6. Improve the explainability and interpretability of the models that have been constructed, taking into account the interpretability issues related to contrastive learning. To increase the models' credibility, explain how particular properties affect the identification of biomarkers.
7. Examine how the modeling approach may incorporate further clinical metadata, such as patient demographics and medical history. Examine how the aforementioned data could improve the precision and customized aspect of identifying ocular biomarkers.

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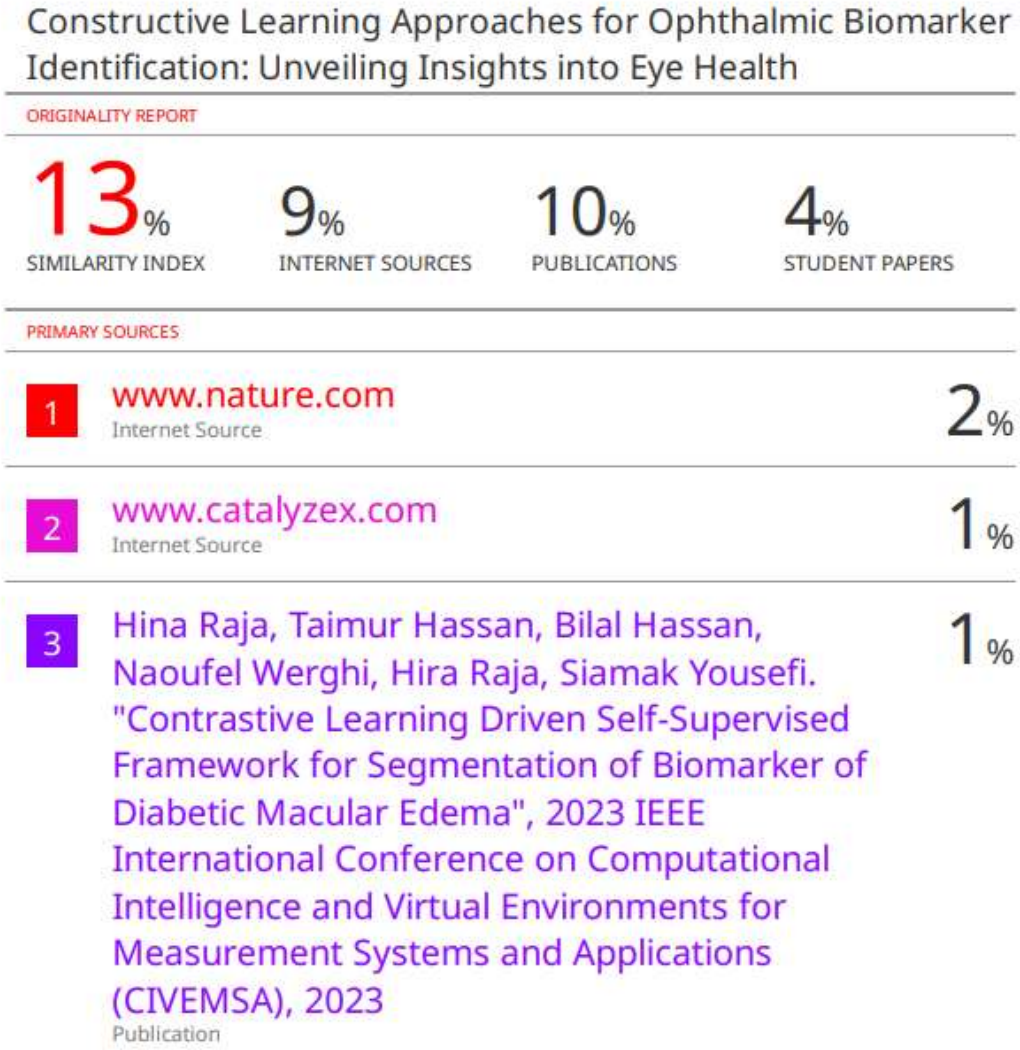

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