

# A Multimodal Approach for Ophthalmic Disease Diagnosis

Minor Project-II Presentation (B.Tech 3rd A.I.)

AIC 3950



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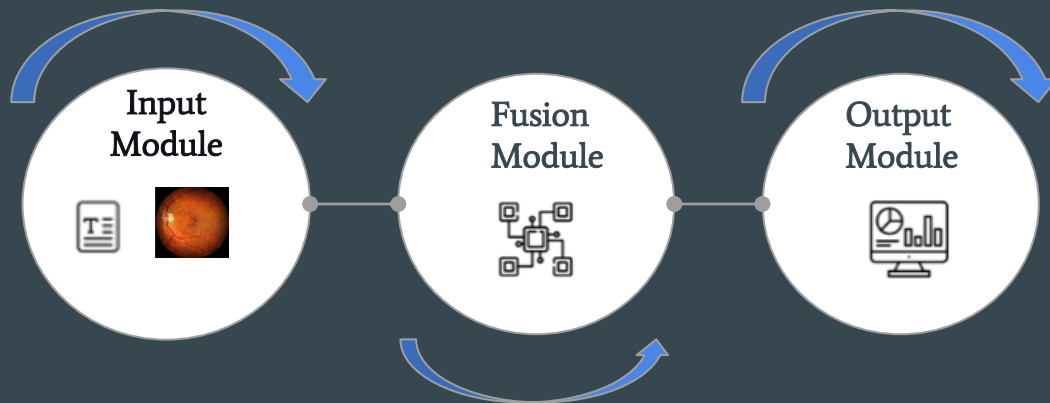
# Introduction

What is Multimodal Learning?

It is a subfield of artificial intelligence that seeks to effectively process and analyze data from multiple modalities.

These systems constitute three fundamental components :

- An input module
- A fusion module
- An output module



# Problem

- **Incompleteness:** Single-source fundus imaging often results in incomplete diagnostics, missing the full complexity of ocular conditions.
- **Accuracy Issues:** Reliance on visual fundus images alone can lead to inaccuracies and diagnostic errors.
- **Diagnostic Bias:** Traditional methods are subject to biases influenced by image quality and interpreter experience.
- **Lack of Integration:** Current diagnostics do not adequately incorporate crucial patient-specific data like demographics and clinical history.
- **A Need for Better Methods:** There is a critical need for a multimodal diagnostic approach that integrates various data types to improve reliability and precision.

# Related Work

- ❖ **Al-Fahdawi et al., (2023)** : Developed Fundus-DeepNet, a sophisticated multi-label deep learning system that integrates enhanced image preprocessing and deep feature extraction techniques to accurately detect multiple ocular diseases.
- ❖ **Ran Xiao et al., (2023)** : Developed a multimodal deep learning model that integrates ECG waveforms and patient demographics to enhance diagnostic accuracy for myocardial infarction, achieving significant improvements in performance.
- ❖ **Keerthiveena et al., (2020)**: Focused on computer-aided diagnosis using feature fusion, underlining the benefit of integrating multiple data sources for enhanced diagnostic accuracy.
- ❖ **Chelaramani et al., (2020)**: Explored multi-task learning to enhance fine-grained eye disease prediction by developing methods for generating textual diagnoses, facilitating a deeper understanding of diagnostic outcomes.

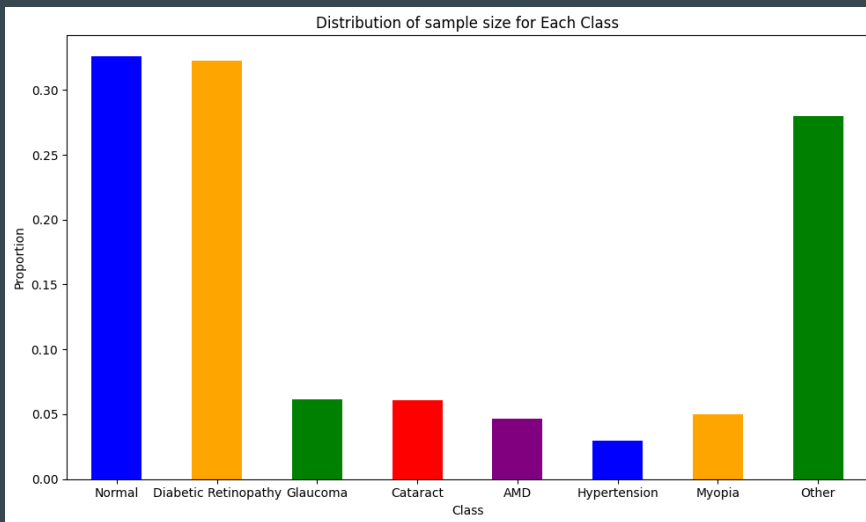
# System Design - The Dataset

A structured ophthalmic database of 5,000 patients with age, color fundus photographs from left and right eyes and doctors' diagnostic keywords from doctors (in short, ODIR). They classify patient into eight labels including normal (N), diabetes (D), glaucoma (G), cataract (C), AMD (A), hypertension (H), myopia (M) and other diseases/abnormalities (O) based on both eye images and additionally patient age.

Training Set : 7000 images (3500 samples)

On-site Test(Validation Set) : 1000 images (500 samples)

Off-site Test( Test Set ) : 2000 images ( 1000 samples)



# System Design - Data Preparation

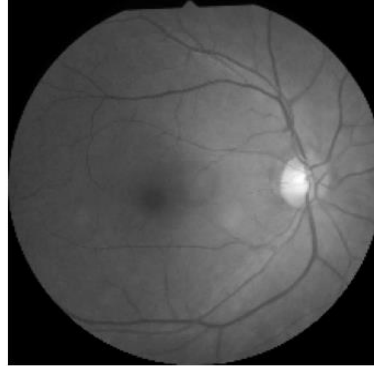
## Preprocessing:

- ☐ Circular border cropping to remove black borders around the eye images.
- ☐ Image resizing to a standard (224x224) pixels.
- ☐ Contrast enhancement using the CLAHE method.
- ☐ Median filter applied for noise reduction.
- ☐ Conversion of images to grayscale to standardize the input.
- ☐ Generation of a clipping mask to extract only the relevant part of the images.

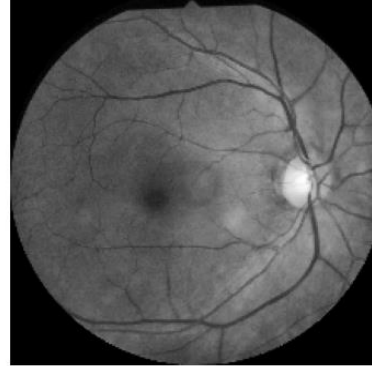
## Enhancement Techniques:

- **Use of CLAHE (Contrast Limited Adaptive Histogram Equalization):**
  1. Operates on small regions in the image (tiles).
  2. Improves the contrast of the images while preserving natural appearance.
- **CLAHE parameters:**
  1. **Clip limit (CL):** 2 for increased brightness.
  2. **Block size (BS):** (8x8) for enhanced contrast and wider intensity range.

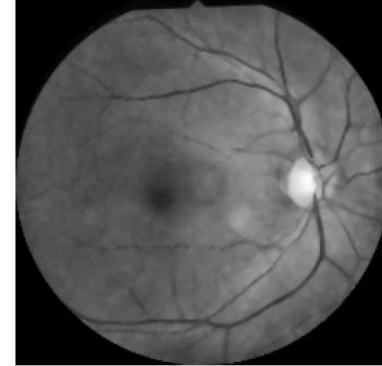
Cropped Region



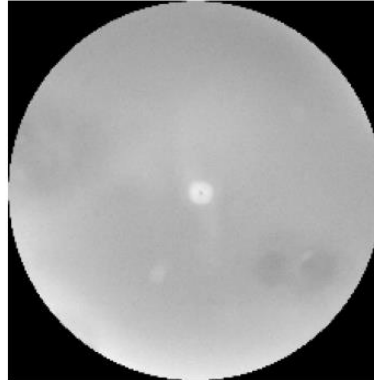
CLAHE Output



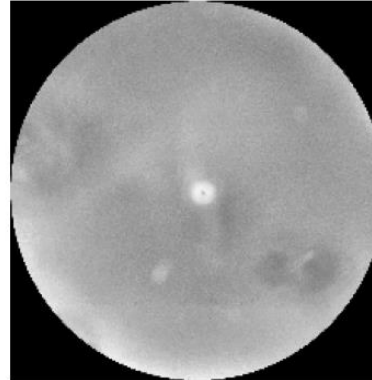
Median Filter Output



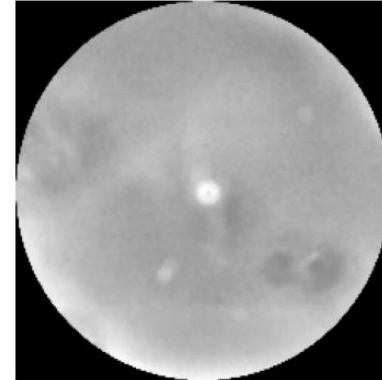
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CLAHE Output



Median Filter Output



# System Design - Original Model Architecture

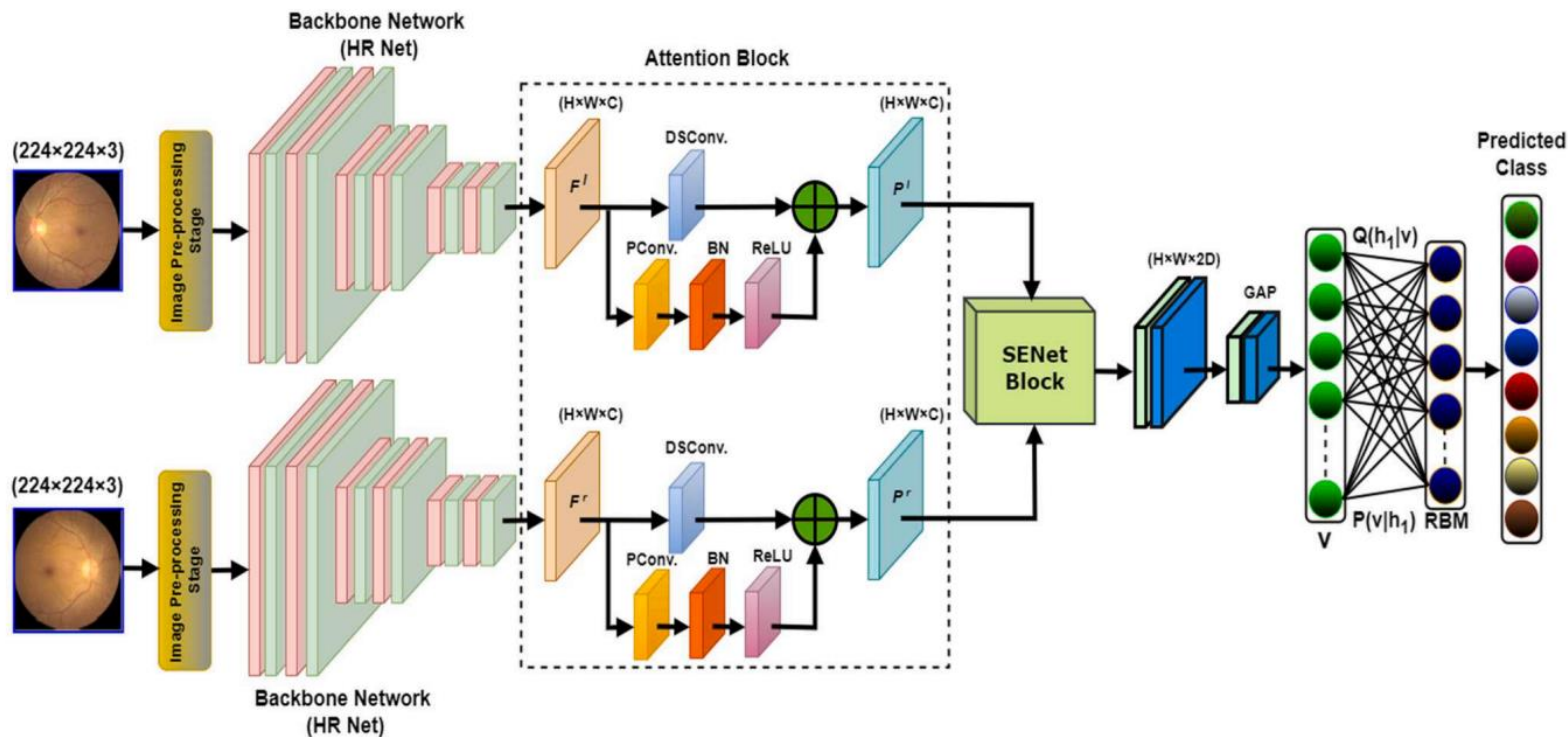
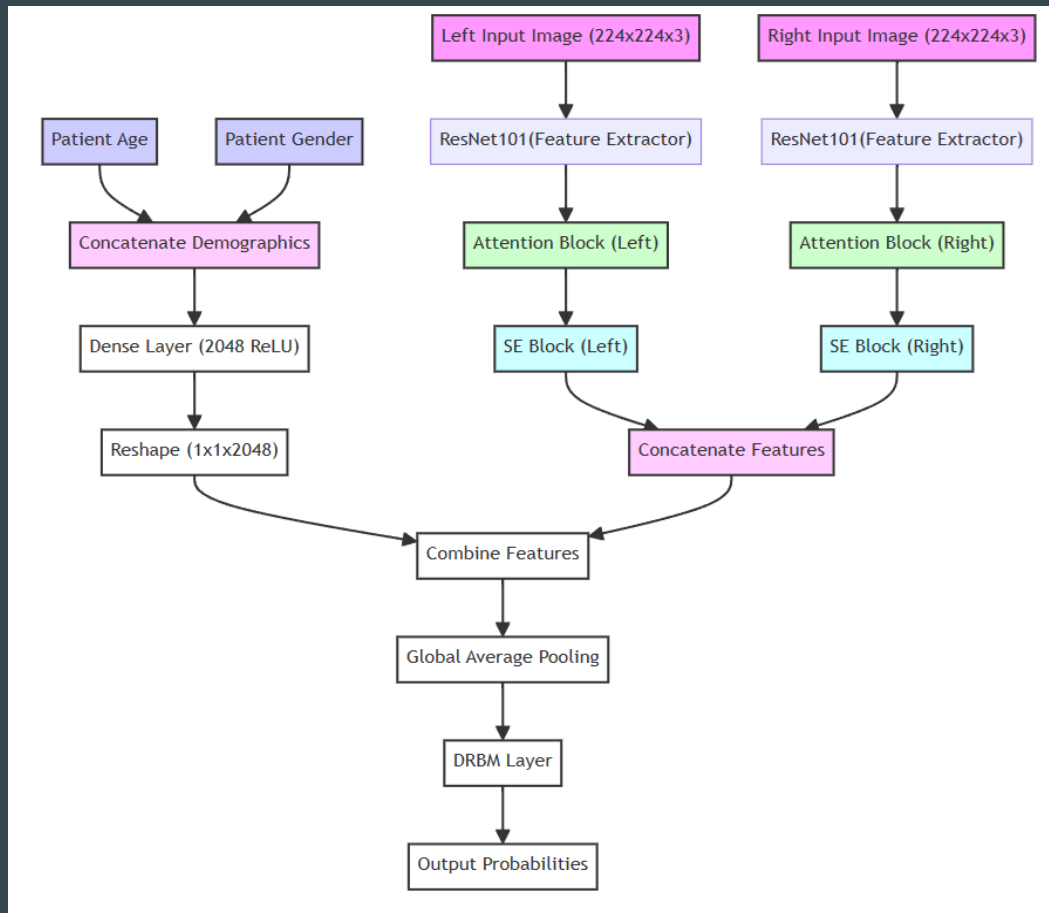


Fig. 1. The diagram illustrating the structure of the proposed Fundus-DeepNet system.

Source: Al-Fahdawi, S., Al-Waisy, A. S., Zeebaree, D. Q. et al. (2024). Fundus-DeepNet: Multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images. Information Fusion, 102, 102059



# System Design - Proposed Model Architecture



# System Design - Late Feature Fusion



## **Fusion-Based Approach**

It involves encoding the different modalities into a common representation space.



## **Alignment-based approach**

This approach involves aligning the different modalities so that they can be compared directly.



## **Late fusion**

This approach involves combining the predictions from models trained on each modality separately.

Source: <https://www.kdnuggets.com>

The type of feature fusion used in our model is **Late Fusion**.

The fusion approach is implemented:

- **Separate Feature Extraction:** Features are extracted independently from both the left and right inputs using possibly the same feature extraction method .
- **Attention and SE Blocks:** Each set of features from the left and right inputs are further processed separately through attention blocks and SE blocks.
- **Concatenation of Features:** The features processed by the attention and SE blocks from both inputs are then concatenated. This is the step of **late fusion** where the combination of features happens late in the process, just before the final decision-making layers.

# System Implementation

## A.I. Retinal Scan Analysis

Unveiling potential diseases with cutting-edge technology.

Age:

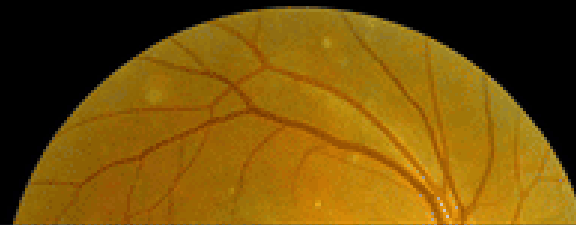
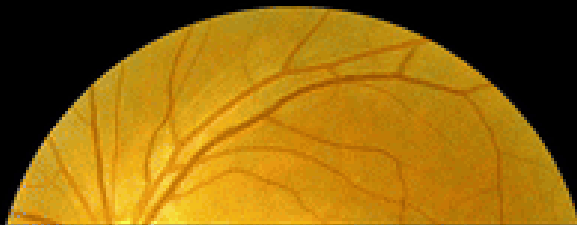
Sex:

Retinal Scan (JPEG or PNG)

Left Retinal Scan:

 9\_left.jpg

Right Retinal Scan:

 9\_right.jpg

# Results

## Testing:

Accuracy Score : 70%

AUC Score : 83%

## Training:

Accuracy Score : 91%

AUC Score : 100%

## Original Results:

Accuracy : 74%

AUC Score : 98%

# References

- Al-Fahdawi, S., Al-Waisy, A. S., Zeebaree, D. Q. et al.(2024).Fundus-DeepNet: Multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images. Information Fusion, 102, 102059. [DOI: 10.1016/j.inffus.2023.102059]
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Thank you for your attention!

Any Questions?