Esemble Model in Retina Classification

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Introduction

Introduction

- What Is The Retina Disease Classification?

- Who Will Use The Classification Model

- What Is The Protential Chanllenge Of The Retina Disease Classification?

- What Is The Solution To The Challenge?

What Is Retina Disease Classification?

- ## Medical Imaging Technologies

  Utilizes tools like Optical Coherence Tomography (OCT) for imaging the retina.

- ## Application of AI

  Employs deep learning and computer vision techniques to automate the identification and classification of retinal diseases.

- ## Disease Identification

  Focuses on distinguishing various retinal abnormalities such as macular degeneration, diabetic retinopathy, and retinal detachment.

- ## Clinical Importance

  Critical for early diagnosis and helps in creating effective treatment plans by allowing precise assessment of retinal health.

Who Will Use The Classification Model?

NO.1

Ophthalmologists

NO.2

Medical Institution

NO.3

Medical Researcher

NO.4

Medical Technology Developer

What Is The Protential Chanllenge Of The Retina Disease Classification

01 **Computational Burden and Processing Time**

02 **Complexity of Models**

03 **Replacing Traditional Diagnostics**

04 **Decision Transparency**

05 **Data Quality**

What Is The Solution To The Chanllenge

VGG-19 A

VGG-19 uses a 19-layer network to extract fine-grained features, suitable for complex medical images. Pre-trained weights help address data imbalance, improving performance on smaller datasets

Inception V3 B

ResNet-50's residual blocks solve deep network degradation, enabling deeper, more accurate models. This structure captures complex features and enhances generalization across diverse datasets.

What Is The Solution To The Chanllenge

My Proposed Solution

RetinaNet-Enhanced

Proposed Solution: RetinaNet-Enhanced combines depthwise CNNs, residual learning, Inception architecture, and wavelet analysis to improve retinal disease classification. Depthwise CNNs provide efficient feature extraction by reducing parameters and computational complexity, while residual learning mitigates the vanishing gradient problem, allowing deeper network training. The Inception architecture captures multi-scale features, improving disease pattern detection, and wavelet analysis enhances feature representation, aiding in the identification of subtle retinal features. This integrated approach effectively addresses challenges like data imbalance, image quality variation, and model generalization, leading to a robust and accurate classification system.

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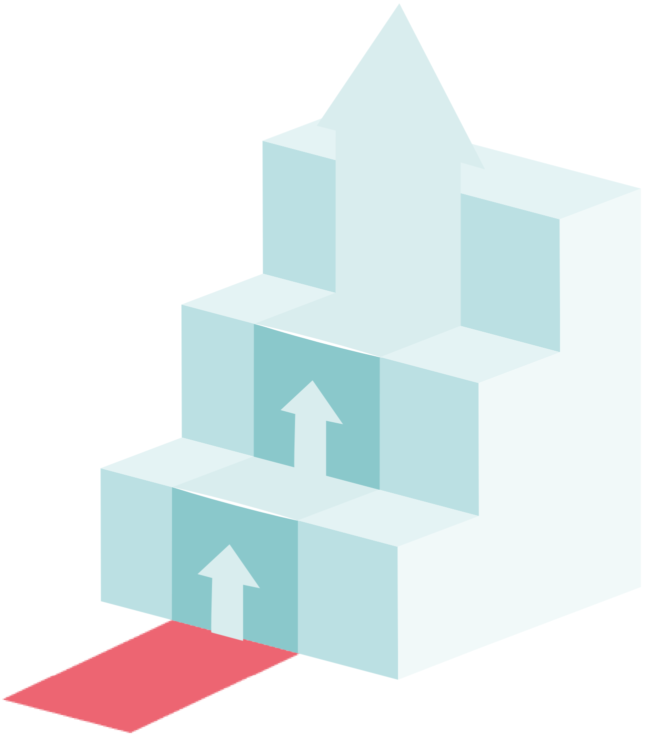
Background

Background

01 Research Challenges

02 Research's Work



Research Challenges

1. Data Quality and Consistency
2. Data Imbalance
3. Model Generalization
4. Interpretability and Transparency
5. Computational Resources
6. Security and Privacy

Research’s Work

Background Research

The background research for this project focuses on advanced deep learning techniques and their application to retinal disease classification. Depthwise CNNs, residual learning, Inception architecture, and wavelet analysis are explored for their efficiency in feature extraction, handling of deep network training issues, capturing multi-scale features, and enhancing feature representation, respectively .

Research Methodology

The methodology includes the use of data augmentation to address data imbalance, resizing and labeling of images, and employing depthwise separable convolutions, residual learning, Inception modules, and wavelet analysis for feature extraction and classification.

03

Dataset

Data Augmentation

- **Rescale:** Normalizes the pixel values of images to a range between 0 and 1.
- **Random Rotation:** Rotates images by a random degree between -20 and 20 degrees.
- **Width Shift:** Shifts images horizontally by up to 20% of the image width.
- **Height Shift:** Shifts images vertically by up to 20% of the image height.
- **Brightness:** Adjusts brightness randomly within 80% to 120% of the original brightness.
- **Random Zoom:** Zooms images in and out to add variation in scale.
- **Horizontal Flip:** Flips images horizontally.
- **Vertical Flip:** Flips images vertically.

Data Augmentation

Technique	Description	Parameters
Rescale	Normalizes pixel values to the range 0-1.	1./255
Random Rotation	Rotates images randomly within a specified range to increase variation.	-20 to 20 degrees
Width Shift	Randomly shifts images horizontally to add positional variation.	Up to 20%
Height Shift	Randomly shifts images vertically to add positional variation.	Up to 20%
Brightness	Adjusts image brightness to simulate different lighting conditions.	80% - 120%
Random Zoom	Zooms in/out on images to introduce scale variation.	Applied randomly
Horizontal Flip	Flips images horizontally to increase diversity.	Applied randomly
Vertical Flip	Flips images vertically to increase diversity.	Applied randomly

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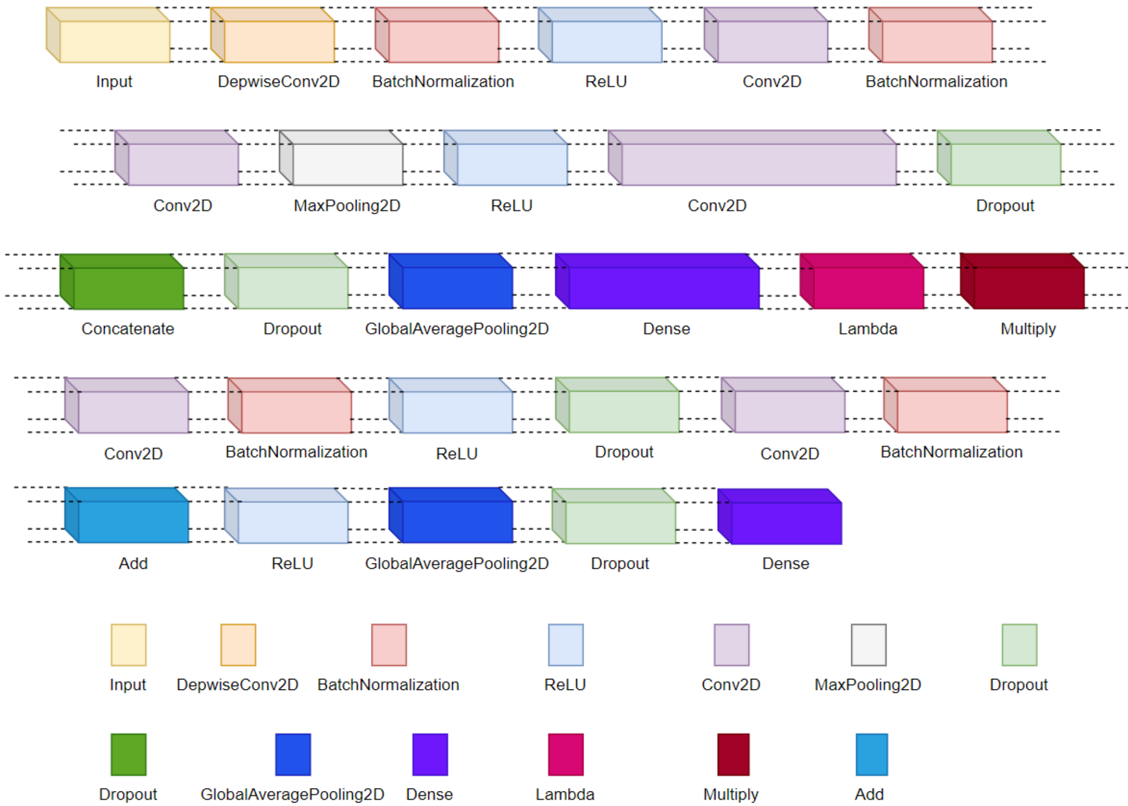
Model Architecture And Resault

Model Architecture



Experiment Design

Stage 1: Epochs Experiment

Parameters	Values
Epochs	30
	50
	100
Input size	224 * 224 * 3
Batch size	4
Optimizer	Adam
Activation function	ReLU
Learning rate	0.001
Global Average Pooling Layers Number	1

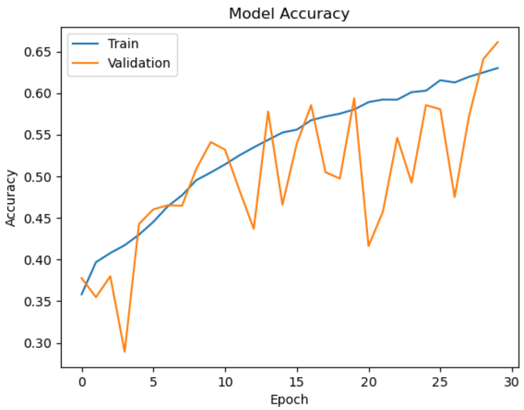
Experiment Design

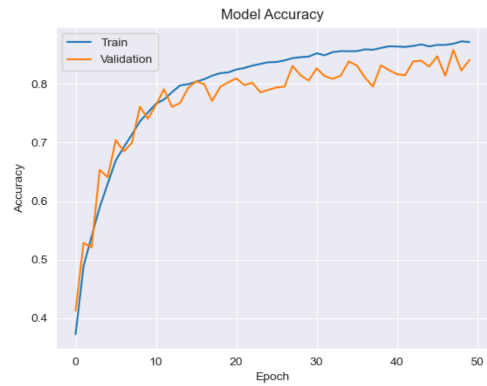
Stage 2: Learning Rate Experiment

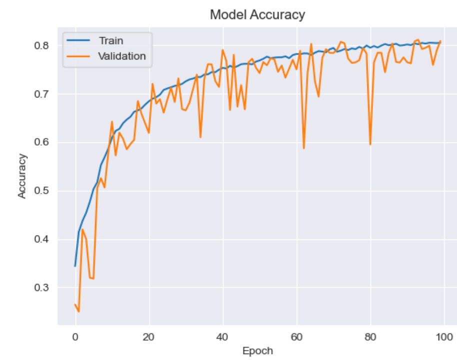
Parameters	Values
Epochs	50
Input size	224 * 224 * 3
Batch size	4
Optimizer	Adam
Activation function	ReLU
Learning rate	0.005
	0.001
	0.0005
Global Average Pooling Layers Number	1

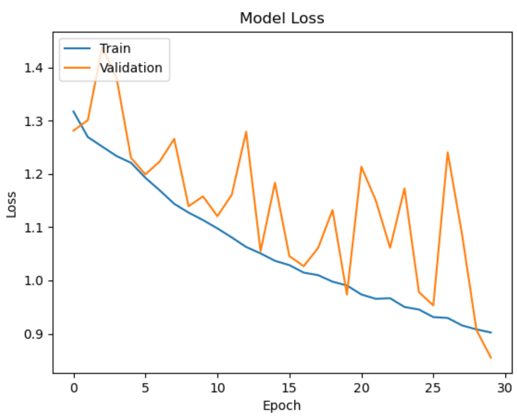
Experiment Resualt

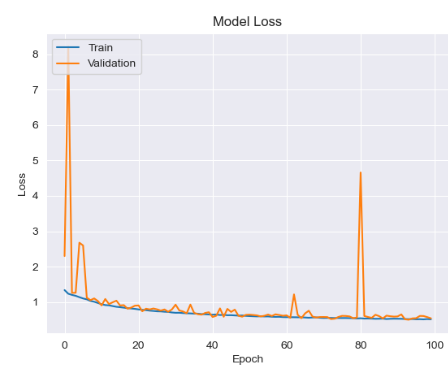
Epochs Experiment Result For 30,80,100 Epoches











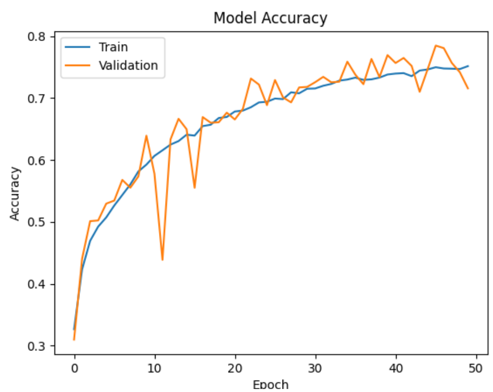
Experiment Resualt

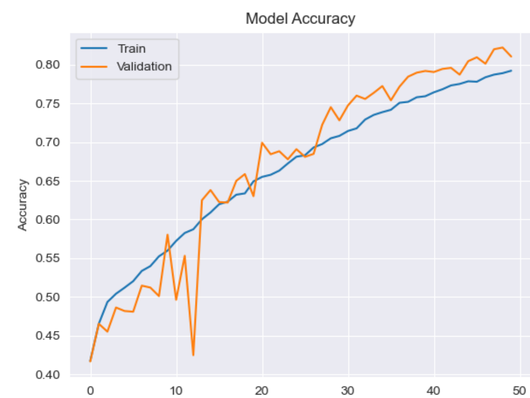
Comparison Table For 30,80,100 Epoches

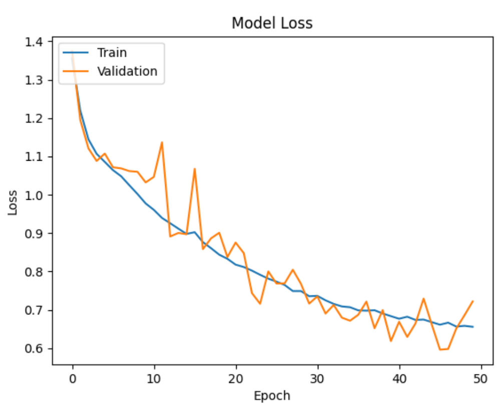
Epoch	Train_Accuracy	Val_Accuracy	Train_Loss	Val_Loss
30	63.02%	66.14%	0.9023	0.8552
50	87.15%	84.07%	0.3588	0.4305
100	80.52%	80.87	0.5165	0.5436

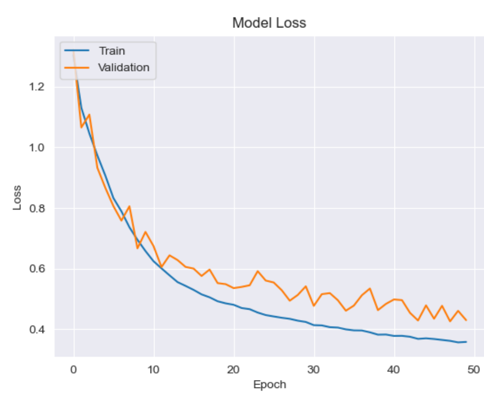
Experiment Resualt

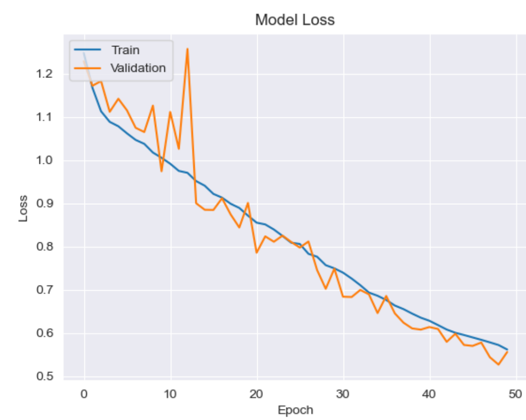
Learning Rate Experiment Result For 0.005, 0.001, 0.0005











Experiment Resualt

Comparison Table For 0.005, 0.001, 0.0005 Learning Rate

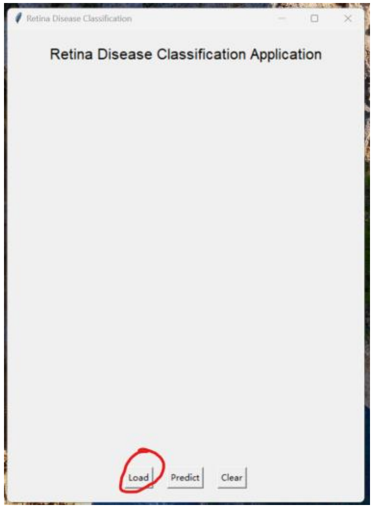
Learning Rate	Train_Accuracy	Val_Accuracy	Train_Loss	Val_Loss
0.005	75.94%	71.65%	0.6611	0.6983
0.001	87.15%	84.07%	0.3588	0.4305
0.0005	79.20%	81.04%	0.5165	0.5436

Experiment Resualt

Total Comparison For Whole Experiment Resualt

Phase	Epoch	Learning Rate	Train_Accuracy	Val_Accuracy	Train_Loss	Val_Loss
Phase 1: Explore the epochs influence on deep learning model performance	30	0.001	63.02%	66.14%	0.9023	0.8552
	50		87.15%	84.07%	0.3588	0.4305
	100		80.52%	80.87	0.5165	0.5436
Phase 2: Explore the learning rate changes influence on the deep learning performance based on the phase 1.	50	0.005	75.94%	71.65%	0.6611	0.6983
		0.001	87.15%	84.07%	0.3588	0.4305
		0.0005	79.20%	81.04%	0.5165	0.5436
Best Result	50	0.001	87.15%	84.07%	0.3588	0.4305

Retina Classification App



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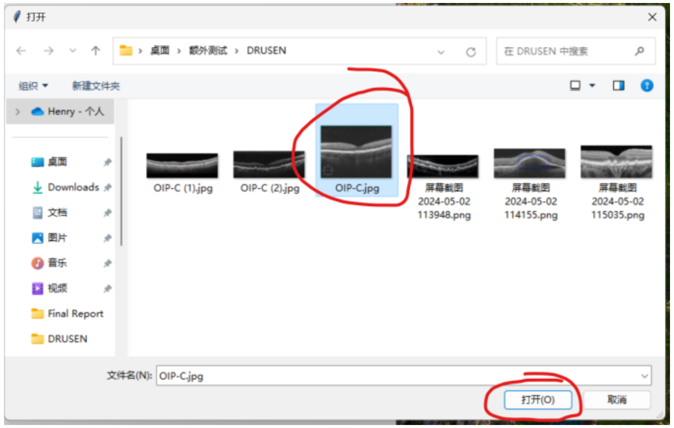

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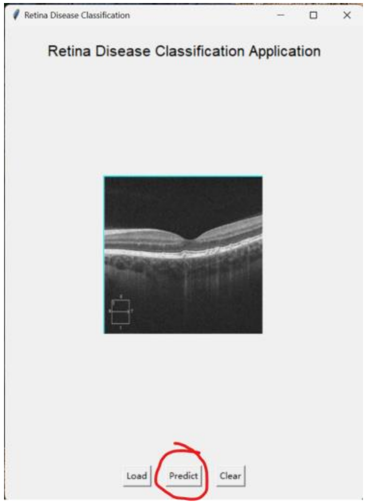

Predict

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Limitation

Limitation Of This Model

- **Potential for Bias**

  Deep learning models, including this one, can exhibit biases which might lead to inaccurate diagnoses for certain patient groups. For example, if the model performs differently for male and female patients, this indicates a potential gender bias. Addressing this requires a thorough examination of the model's fairness and ensuring decisions made by the algorithm are transparent.

- **Need for Rigorous Quality Control**

  Ensuring the model's accuracy and reliability in clinical settings necessitates stringent quality control and validation procedures. This involves routine inspections and adjustments to align the model with the latest clinical standards, employing methods such as cross-validation and using external validation sets to assess performance.

- **Ethical and Social Considerations**

  When deploying deep learning models in medical diagnosis, it is crucial to consider social obligation and fairness. Poor performance in specific demographic groups can lead to healthcare disparities. The design and implementation of the model must adhere to principles of social justice to minimize potential negative impacts on specific demographic groups .

- **Clinical Importance**

  Training complex deep learning models requires substantial computational resources, which can have adverse environmental impacts. This includes the significant use of electrical and cooling resources needed for the training process. This environmental concern should be addressed by optimizing resource usage and considering the ecological footprint of model training

05

Conclusion

Conlusion

- **Model Development:** Successfully developed a sophisticated deep learning model for retina disease classification.
- **Techniques Used:** Utilized depthwise convolutional neural networks, residual learning, Inception architecture, and wavelet analysis.
- **Optimization:** Model performance optimized with 50 epochs and a learning rate of 0.001 through detailed experimentation.
- **Future Improvements:**
  - Explore advanced techniques like transformers.
  - Enhance data augmentation methods.
  - Apply transfer learning using pre-trained models.
  - Incorporate interpretability methods like attention maps.
  - Use more data for model training

THANK YOU

Q and A Section