RETINAL IMAGE CLASSIFICATION USING SELF-SUPERVISED LEARNING

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Wednesday 9$^{\text{th}}$ October, 2024

1 Introduction

Retinal diseases such as diabetic retinopathy, glaucoma, and macular degeneration affect millions globally. Early detection through automated retinal image analysis can significantly reduce the risks of vision loss. However, developing machine learning models that are reliable and efficient for medical image classification remains a challenge due to the limited availability of labeled data. Traditional supervised learning approaches rely heavily on annotated datasets, which are costly and time-consuming to produce, especially in the medical field [3].

This project addresses this limitation by employing self-supervised learning (SSL) using unsupervised reconstruction techniques to train a model for retinal image classification [2]. By focusing on reconstruction loss, the model learns meaningful representations of the retinal images and distinguishes between healthy and unhealthy retina without the need for extensive labeled data. The performance of the model is evaluated using log loss, which measures how well the model reconstructs the input images[6].

2 Dataset

Three datasets are used for training and evaluation, each contributing unique properties to enhance the generalization and robustness of the model:

FLoRI21 Dataset: Comprising high-resolution TIFF images of the retina, this dataset is small but contains high-quality retinal images with varying pathologies. Due to the small size, overfitting is a concern, and careful regularization techniques is employed to mitigate it [4].

FIRE Dataset: This dataset includes retinal images with different fields of view and various pathologies. The larger size and diversity of the FIRE dataset helped improve the model's robustness and ability to generalize across different retinal image types [1].

EyePACS Dataset: This dataset provided a broader collection of retinal images, further contributing to the variety in the training data. However, EyePACS does not come with labels, making it ideal for self-supervised training and testing the effectiveness of unsupervised reconstruction techniques [5].

The combination of these three datasets allowed the model to learn more diverse and generalized features, improving the ability to detect various retinal conditions.

3 Model Architecture

The architecture for this project is based on a **Convolutional Autoencoder (CAE)**, focusing on unsupervised learning through reconstruction loss. The model is designed to learn compressed representations of the input images (encodings) and then reconstruct the original image from these encodings. The primary goal is to minimize the mean squared error (MSE) between the reconstructed images and the input images, thereby learning meaningful features from the input data. The architecture is divided into two main components:

Encoder: The encoder compresses the input images into a latent space representation using a series of convolutional and pooling layers. The encoded representation captures essential features while reducing the spatial dimensions of the images.

Decoder: The decoder reconstructs the original image from the latent space representation. It employs transposed convolution layers to upsample the compressed features back to the original image size.

The reconstruction loss, measured using mean squared error (MSE), serves as the primary training objective. Figure 1 explains the workflow of the model.

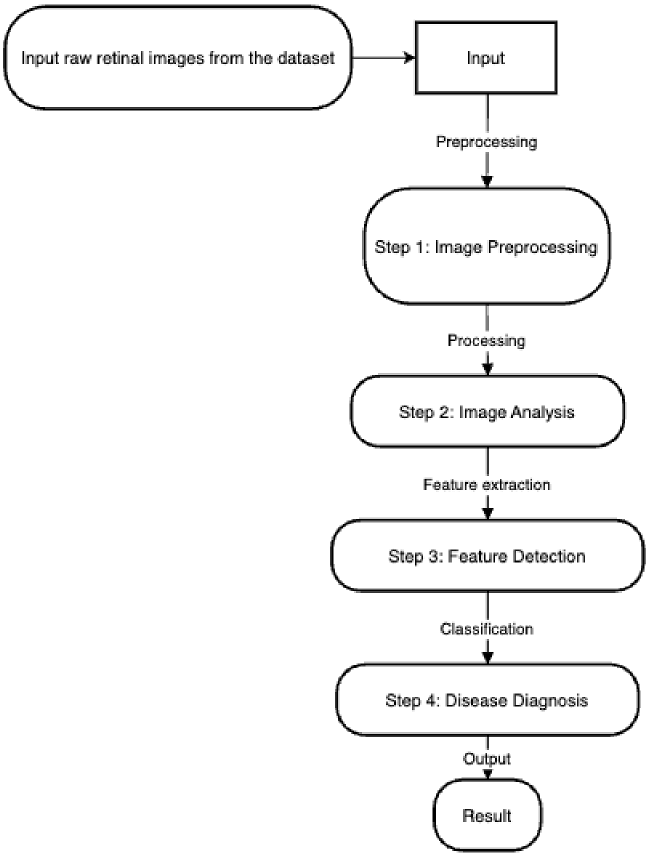

Figure 1: Workflow of Retinal Classification model

4 Results

The model is trained on each dataset individually to evaluate its performance using log loss as the primary metric. The results below show the log loss over 40 epochs for each dataset:

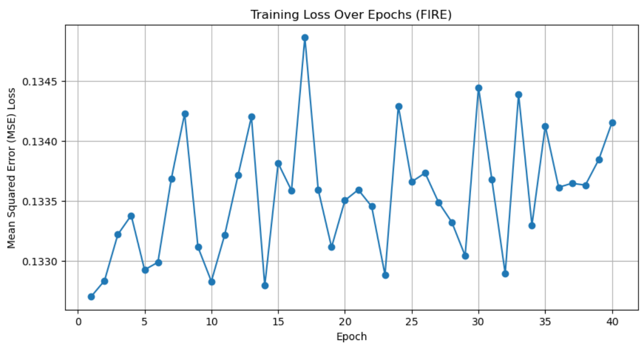

Figure 3: Log loss using FIRE dataset

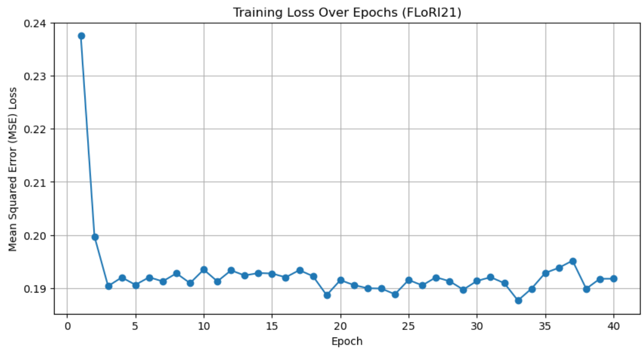

Figure 2: Log loss using FLoRI21 dataset

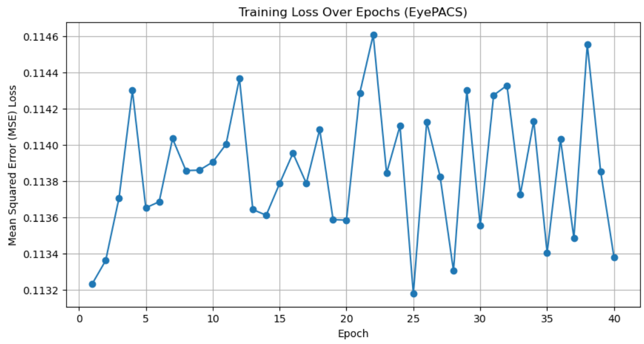

Figure 4: Log loss using EyePACS dataset

- Training Observations: The model demonstrated improved performance across all datasets, with a reduction in log loss as the number of epochs increased.
- The EyePACS dataset yielded the lowest log loss due to its large variety of images, which allowed the model to generalize better.
- Despite the smaller size of the FLoRI21 dataset, the model successfully minimized reconstruction error, though overfitting is a potential challenge.

5 Challenges

Several challenges are encountered during the project, including:

Small Dataset Size: The FLoRI21 dataset contained fewer images, which raised concerns about overfitting. Regularization techniques such as dropout are applied in the decoder layers to address this issue.

Image Preprocessing: The varying resolutions and file formats of images from different datasets necessitated preprocessing to standardize the input. Image augmentation techniques like resizing, random flipping, and rotation are employed to enhance the model's generalization ability.

Evaluation Metrics: Given the unsupervised nature of the task, traditional classification metrics such as accuracy are not applicable. Instead, log loss and MSE are used to evaluate the model's performance in reconstructing retinal images.

6 Conclusion

This project demonstrates that self-supervised learning, particularly using a Convolutional Autoencoder, can effectively classify retinal images based on their health status without requiring labeled data. The model successfully reduced reconstruction error across three diverse datasets, suggesting that unsupervised learning can be a viable solution for medical image analysis where labeled data is scarce. The primary focus on log loss provided an alternative metric for evaluating performance, offering insights into how well the model learned to reconstruct retinal images. While this approach shows promise, future work could explore hybrid methods combining self-supervised learning with a small amount of labeled data to further refine the model's diagnostic capabilities.

References

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