VesselSegNet:A Deep Learning Framework for Autonomous Retinal Blood Vessel Segmentation on Fluorescein Angiography Scans

By

Vishal Balaji Sivaraman

Agenda

- Project Overview
- Proposed Model & Algorithm Summary
- Project Outcome & Demo

Project Overview

- Introduction
- Objective
- Dataset Description

Introduction

Introduction

- The retina is the light-sensitive layer located in the back of the eye that enables vision. In addition, the retina gets oxygen and nutrients from the retinal blood vessels and the choroid.
- A majority of illnesses pertaining to the eye is caused either by retinal blood vessels being leaky or obstructed .As a consequence of this the corresponding section of the vision field will be impaired.
- This occurrence is generally known as an occlusion. There are many conventional deep learning algorithms to examine and procure critical information regarding blood vessels in the retina, but none is more popular than a fully connected convolutional autoencoder, often known as UNet.

Objective

Objective

Short term Objective

To automate the identification and isolation of retinal blood vessels with simplicity and effectiveness.

Long term Objective

To develop an application/tool to assist doctors and surgeons in comprehending the blood flowing through these blood vessels for issue diagnosis.

Dataset Description

Dataset Description

- ✓ In this research, a custom database for segmenting retinal blood vessels was developed by integrating multiple prominent open-source datasets to promote heterogeneity and flexibility.

- ✓ In addition, the datasets 'ARIA', 'ChaseDB', 'DR-Hagis', 'DRIVE', 'HRF', 'IOSTAR', and 'ORVS' were employed for model training and testing, whilst the dataset 'STARE' [7] was utilized for model validation.

Dataset Description

- Moreover, each discrete dataset employed form model training comprises of approximately 20 to 30 exceptional fluorescein angiography (fundus) scans with their respective masks spread across the folders titled train and test respectively, resulting in a custom training database housing approximately of 760 fluorescein angiography (fundus) scans and their corresponding masks for model analysis.
- Finally, the dataset dubbed 'STARE' comprises of roughly 397 exemplary fluorescein angiography (fundus) scans from which five fundus scans selected at random make up the validation database for model validation.

Proposed Model & Algorithm Summary

- Model Description
- Data Modelling & Augmentation
- Proposed Model Architecture
- Proposed Algorithm Workflow Chart
- Proposed Model Framework
- Data Loader Overview
- Proposed Algorithm Design
- Model Metrics

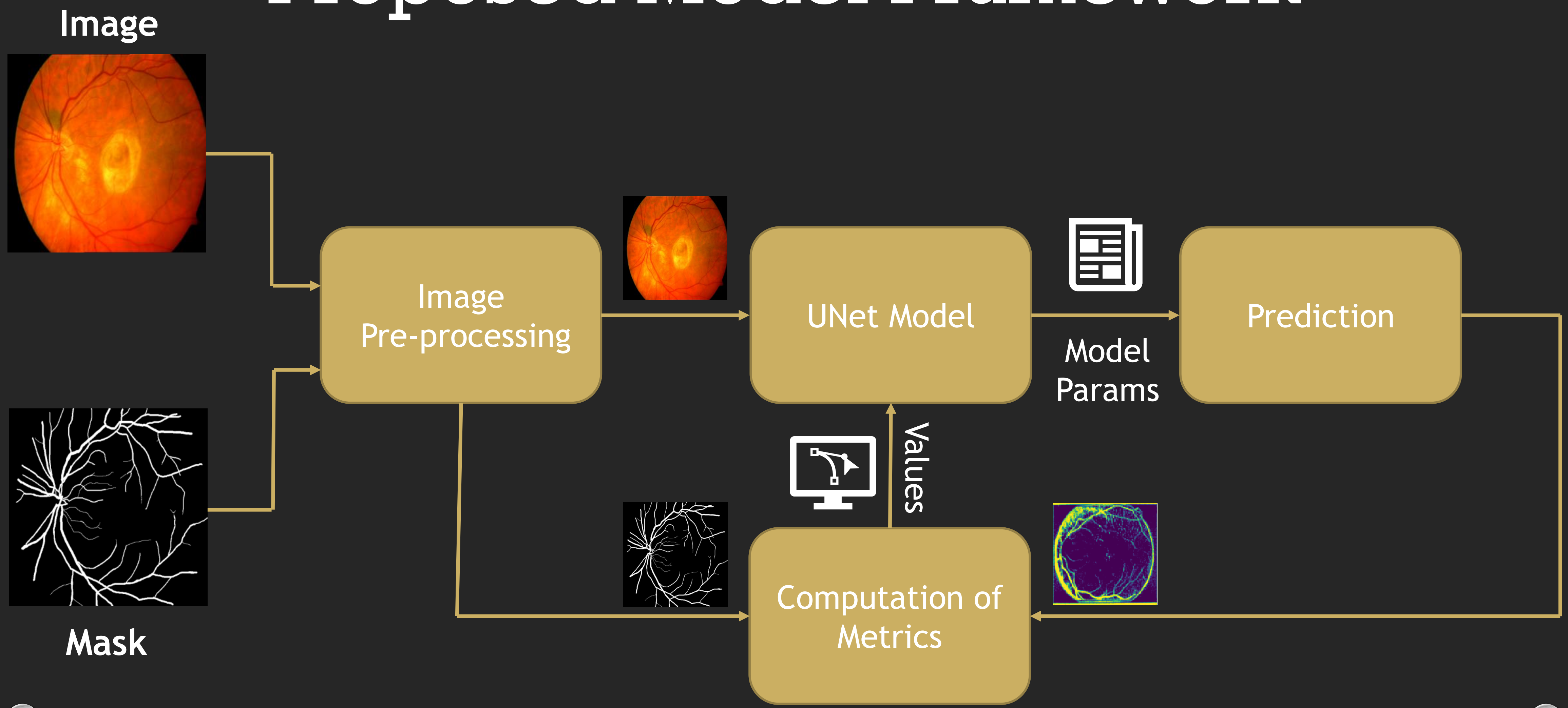
Model Description

Model Description

- The suggested architecture is based on a fully convolutional network, which has been modified and enhanced to operate with less training images and provide more precise segmentations, thereby augmenting our understanding about the region of interest.
- Furthermore, its unique architecture provides precise localization, making it preferable than a typical convolutional neural network.
- Moreover, the suggested network provides critical features such as compatibility, customizability, adaptability, and much more , thereby making it more attractive to machine learning researchers in the field of Medical Imaging.

Proposed Model Framework

Proposed Model Framework



Data Modelling & Augmentation

Data Modelling & Augmentation

- Data modelling is essential for training a deep learning framework prior to deployment. Moreover, the steps are outlined below.
- Initially the images and its corresponding masks spanned across the datasets were resized to an uniform size of **512*512** respectively.
- Concurrently , the resized images and their corresponding masks were also converted to **RGB and Greyscale** before being saved with a universal file extension titled ‘**Portable Network Graphics**’ or **PNG** separately.
- Moreover, the steps were implemented in order to ensure **data uniformity** prior to model training and validation.

Data Modelling & Augmentation

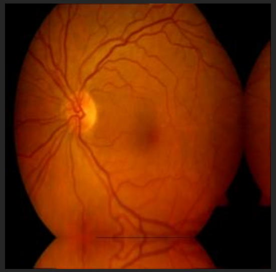
- Furthemore, the preprocessed images and its corresponding masks were introduced to a list of data transformation techniques titled **Horizontal Flip, Vertical Flip, Elastic Transform, Grid Distortion & Optical Distortion,** respectively .
- This step is performed in order to exploit the symmetric nature of the images and its corresponding masks ,thereby augmenting the model's ability to comprehend and generalize, respectively.
- Finally, the step labeled **data augmentation** was only applied to the datasets labelled for model training and validation and not real time validation (RTV) respectively.

Data Modelling & Augmentation Results

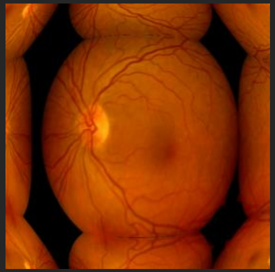
Horizontal Flip

Vertical Flip

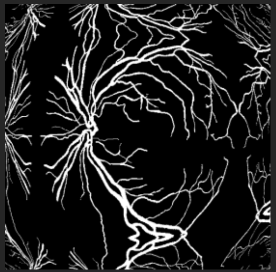
Elastic Transform



Grid Distortion



Optical Distortion



Data Loader Overview

Data Loader Overview

Split	Datasets Employed	Number of Fundus Scans
Training	7	1608
Testing	7	672
Validation	1	5

Proposed Model Architecture

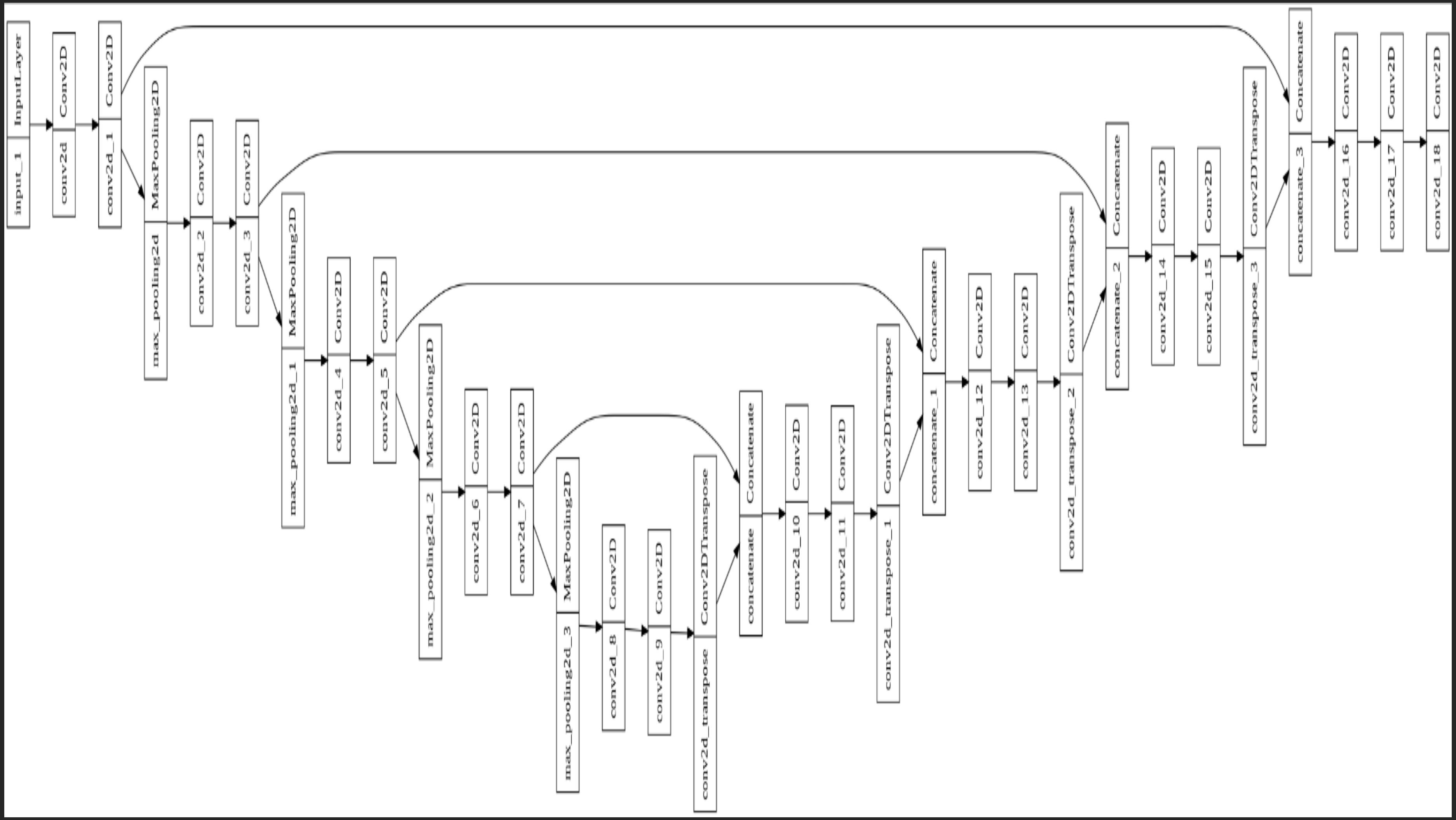
Proposed Model Architecture

- As previously disclosed, a conventional UNet model was utilized to efficiently segment the retinal blood vessels spanning a given fundus image.
- The presented UNet Model comprises of four distinct encoder and decoder blocks connected by a single convolution block that serves as a bottleneck layer in the model.
- Moreover, the proposed convolution block includes two convolutional layers with a Scaled Exponential Linear Unit or 'SELU' activation function and a LeCun initializer , respectively.

Proposed Model Architecture

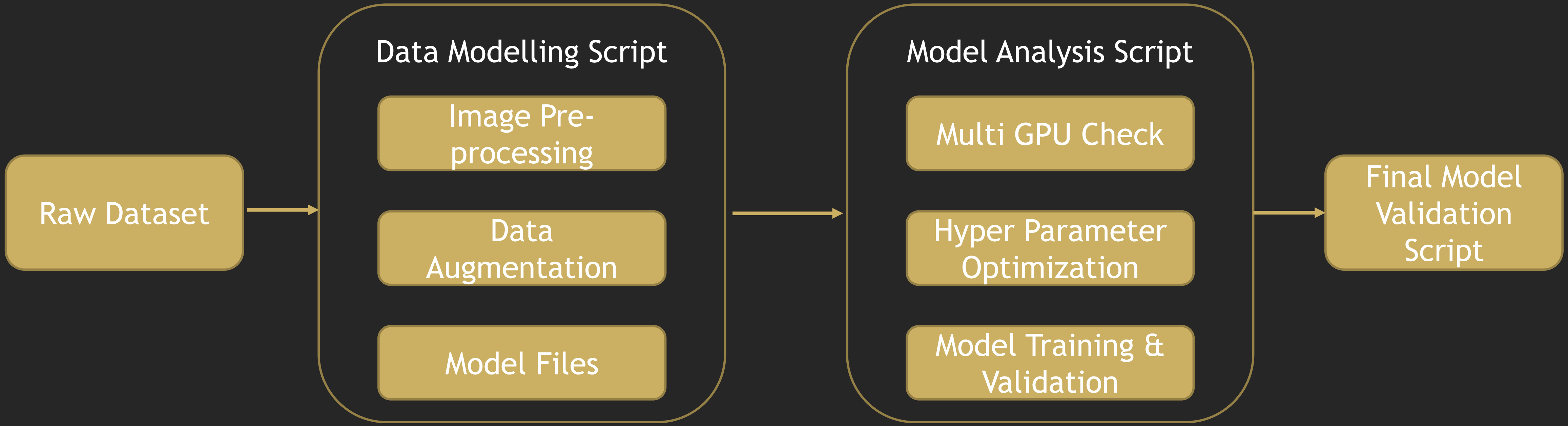
- In addition, each combination of encoder and decoder blocks incorporates a discrete set of convolution blocks with a distinct set of input features.
- Finally, a single convolutional Layer featuring a single neuron and a sigmoid activation function serves as the output layer for the provided model.

Proposed Model Architecture



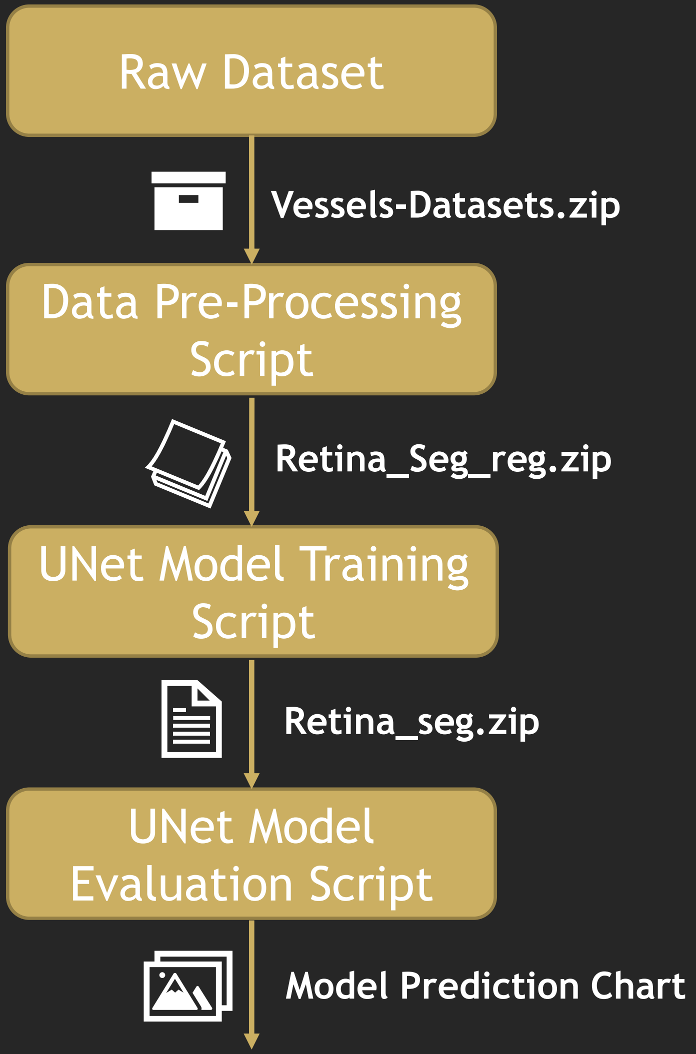
Proposed Algorithm Design

Proposed Algorithm Design



Proposed Algorithm Workflow Chart

Proposed Algorithm Workflow Chart



Model Metrics

Model Metrics

- The suggested system was assessed largely utilizing various metrics dubbed Dice Similarity Coefficient, Dice Loss, Intersection Over Union Precision, and Recall.

- The Dice similarity coefficient is a statistical tool that calculates the similarity between two sets of data, while the dice loss is calculated by subtracting the aforementioned dice coefficient by one.

Model Metrics

- Furthermore, Intersection Over Union (IoU) is a number that measures the degree of overlap between two images, hence the measure is determined in the suggested project by assessing the overlap of the ground truth and projected region verified by the model.

- Moreover, the model’s precision score, or ppv, is defined as the ratio of correctly classified positive samples (True Positive) to the total number of classified positive samples . Finally, the model's recalls score, or TPR, is defined as the model's ability to recognize positive samples.

Model Metrics Formulae Chart

$$\frac{2 * |X \cap Y|}{|X| + |Y|}$$

Dice Coefficient

$$d = 1 - \frac{2|X \bigcap Y|}{|X| + |Y|}$$

Dice Loss

$$IOU = \frac{\text{area of overlap}}{\text{area of union}}$$

Intersection Over Union

$$\textbf{Precision} = \frac{\textit{True Positives}}{\textit{True Positives} + \textit{False Positives}}$$

Precision

$$\textbf{Recall} = \frac{\textit{True Positives}}{\textit{True Positives} + \textit{False Negatives}}$$

Recall

Project Outcome & Demo

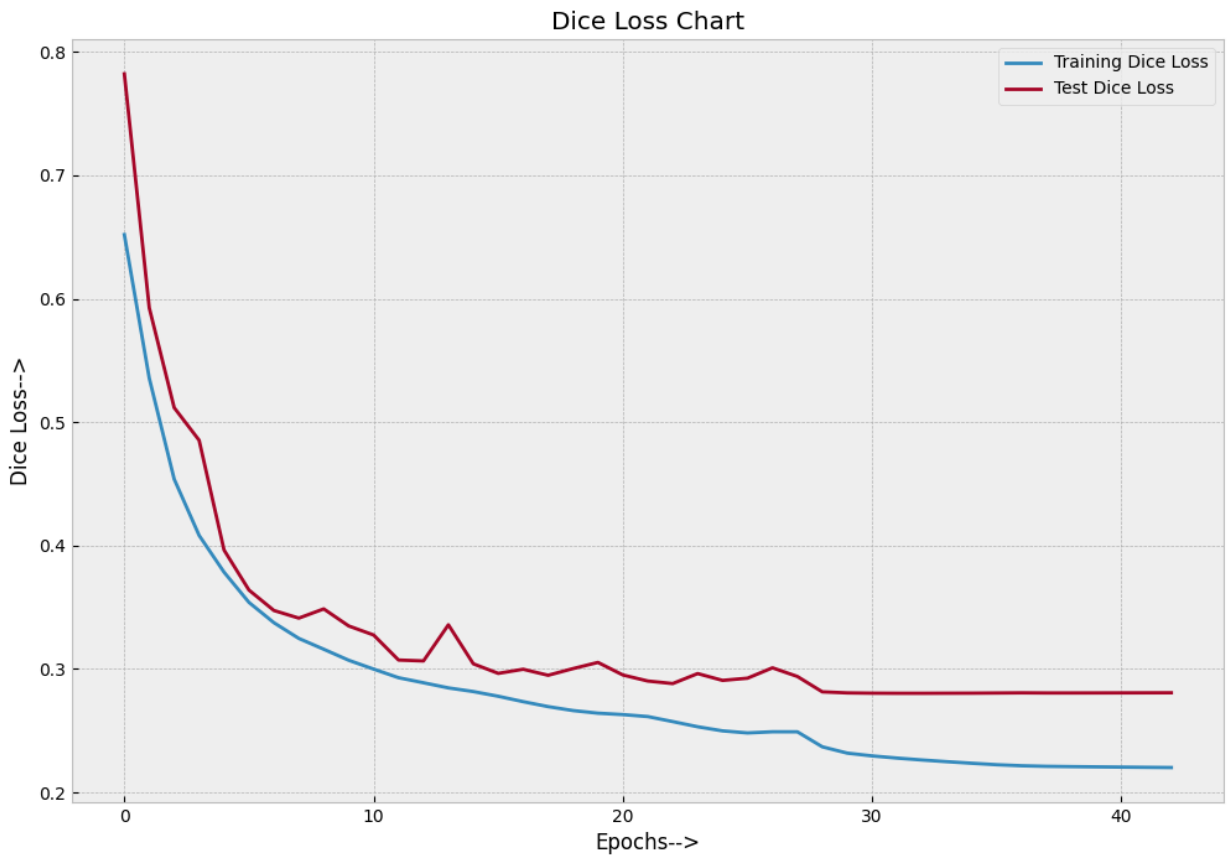
- Model Results & Predictions
- Conclusion & Future Scope
- Project Demo

Model Results

- Dice Loss
- Dice Coefficient
- Intersection Over Union
- Precision-Recall

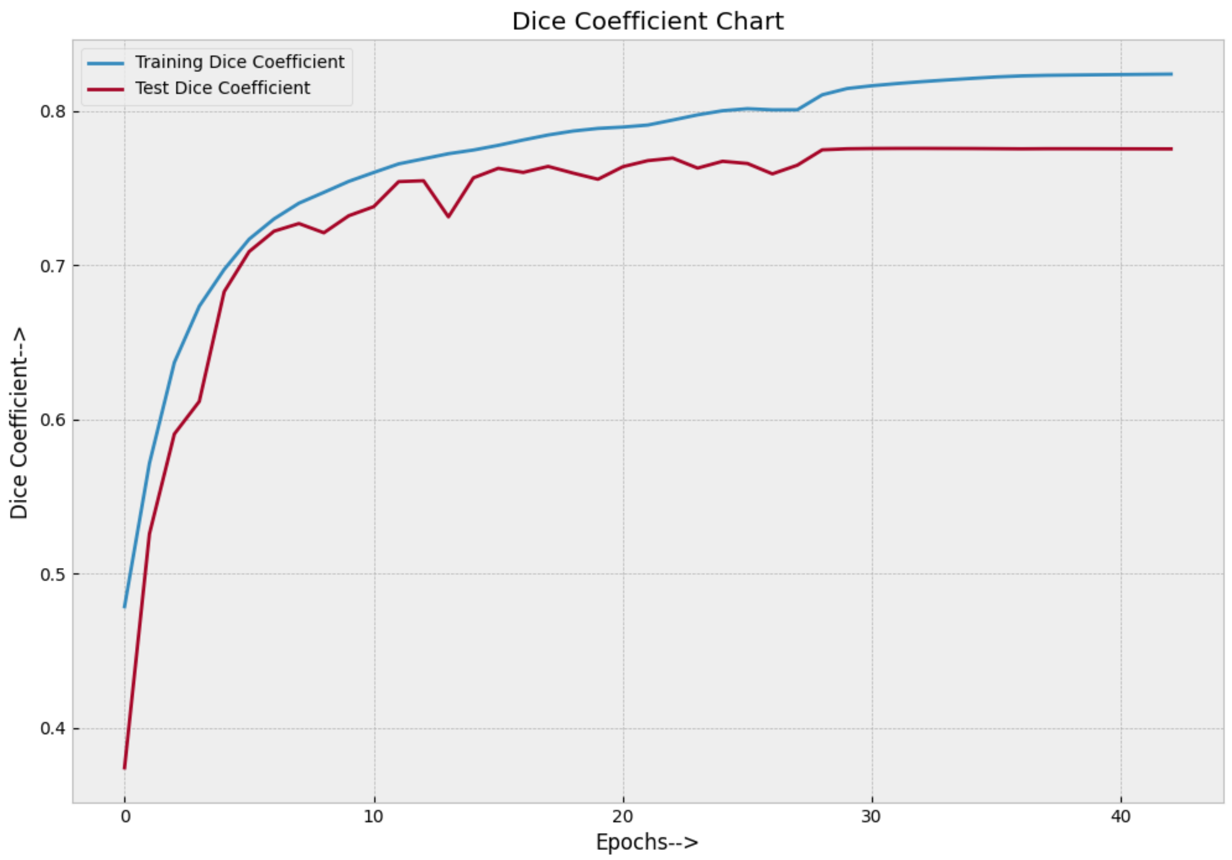
Dice Loss

Dice Loss Results



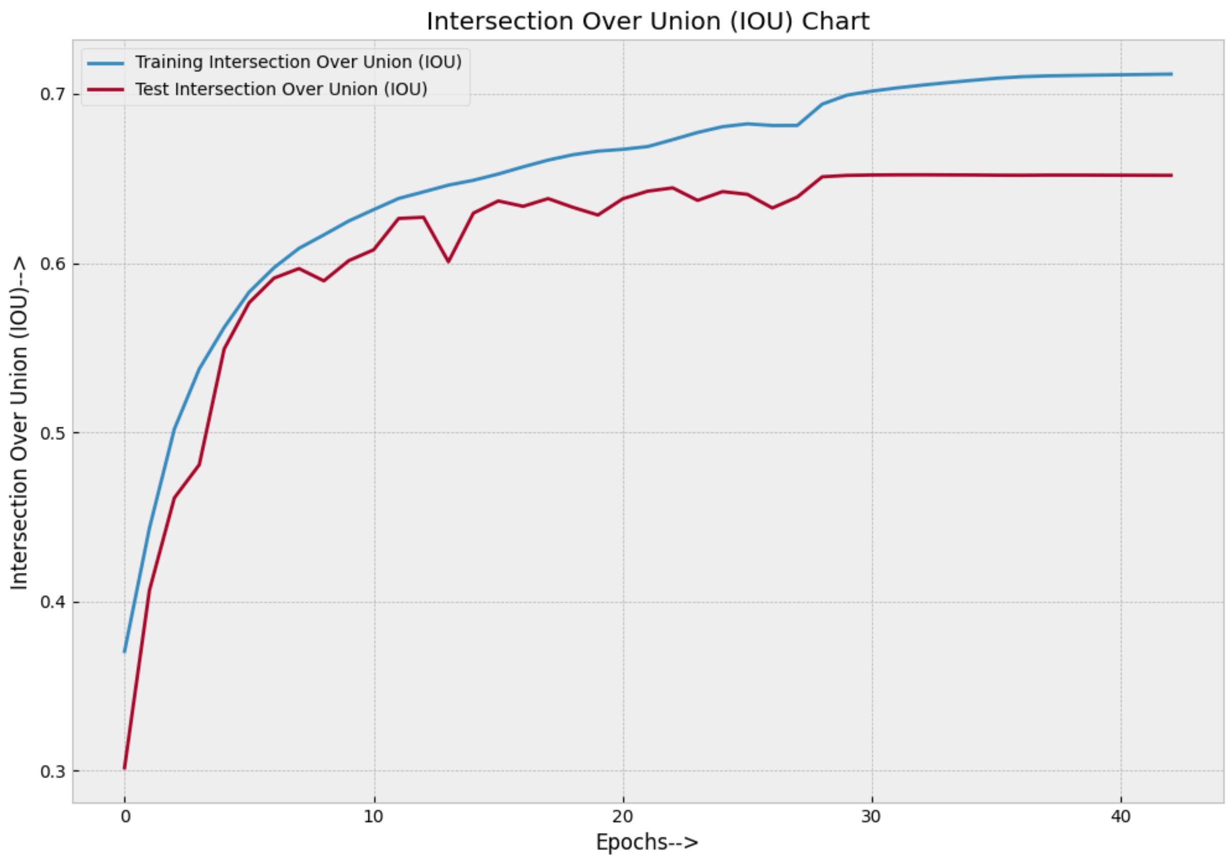
Dice Coefficient

Dice Coefficient Results



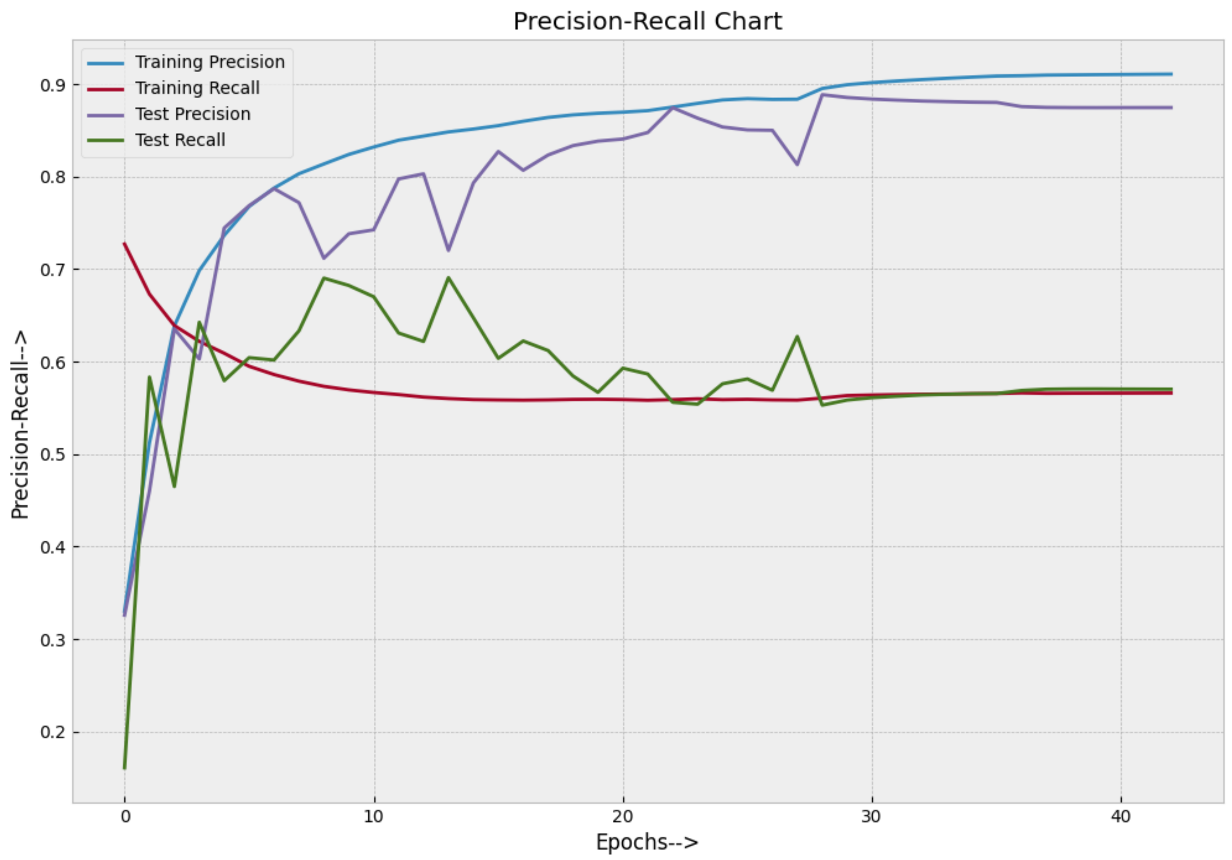
Intersection Over Union

Intersection Over Union Results



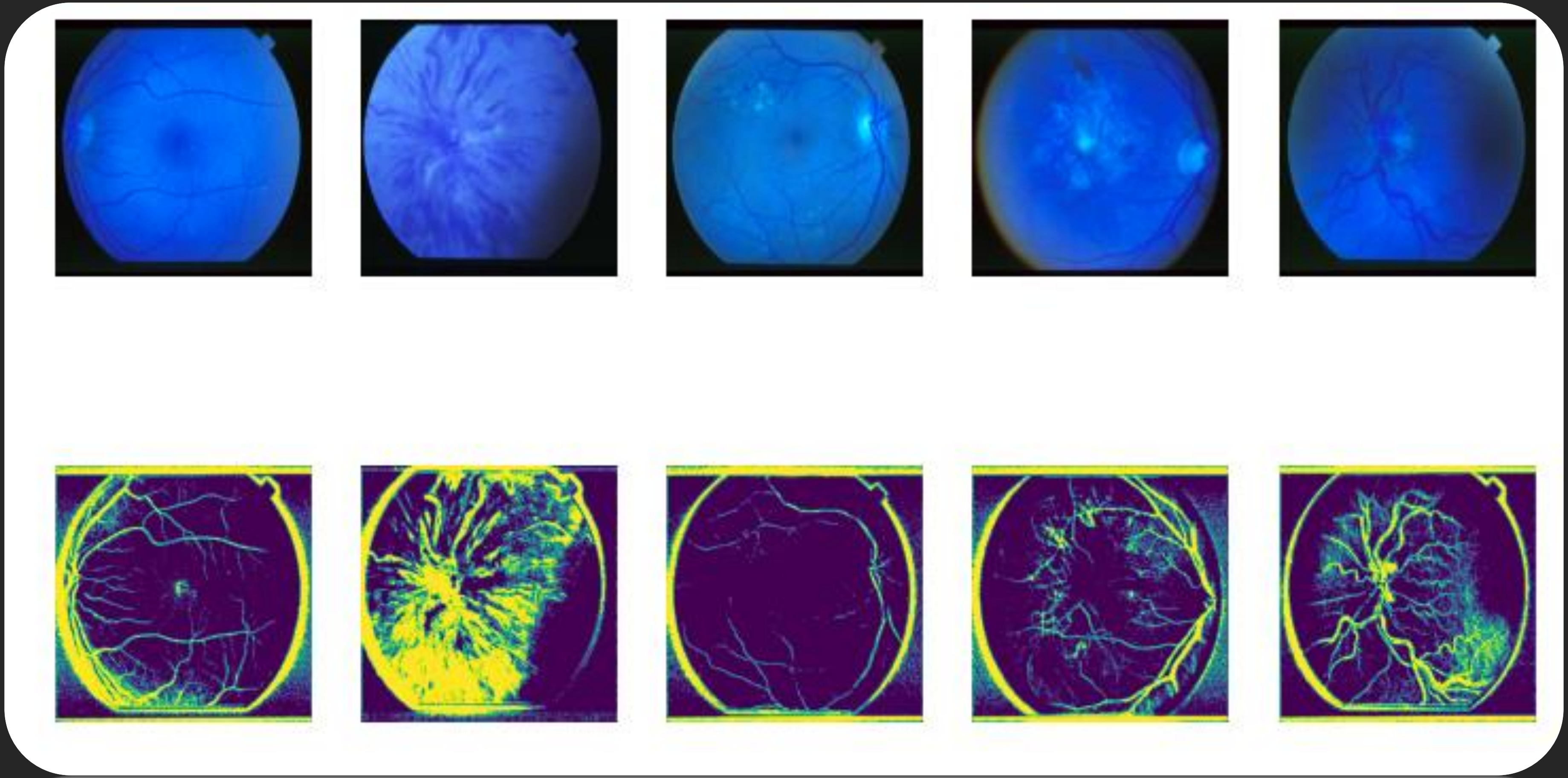
Precision- Recall

Precision- Recall Results



Model Prediction

Model Prediction



Conclusion & Future Scope

Conclusion & Future Scope

- Based on the results, it is possible to conclude that the proposed model framework outperforms state of the art deep learning models in terms of segmenting the Retinal Blood Vessels with ease and efficiency on the presented datasets.

- In addition, the proposed model framework was trained on a Multi GPU Framework (i.e. trained on five GPU's), substantially reducing the time required for training and validating the model while augmenting its performance.

Conclusion & Future Scope

- Nevertheless, there is still room for advancement; consequently, one significant enhancement would be to expand the scope of the model, i.e., train and validate the proposed model framework on a vast variety of datasets to promote diversity while preserving model integrity.

Project Demo

Thank You