A

PROJECT REPORT

ON

"Segmentation of Retinal Fundus image using U-net model"

SUBMITTED TO

SHIVAJI UNIVERSITY, KOLHAPUR

IN THE PARTIAL FULFILLMENT OF REQUIREMENT FOR THE AWARD OF DEGREE BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING

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UNDER THE GUIDANCE OF

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DKTE

Promoting Excellence in Teaching, Learning & Research

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DKTE SOCIETY'S TEXTILE AND ENGINEERING INSTITUTE, ICHALKARANJI

2021-2022

D.K.T.E. SOCIETY'S

TEXTILE AND ENGINEERING INSTITUTE, ICHALKARANJI
(AN AUTONOMOUS INSTITUTE)

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

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Teaching, Learning & Research

CERTIFICATE

This is to certify that, project work entitled

"Segmentation of Retinal Fundus image using U-net model"

is a bonafide record of project work carried out in this college by

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EXAMINER: ________________

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DECLARATION

We hereby declare that, the project work report entitled "**Segmentation of Retinal Fundus image using U-Net model**" which is being submitted to D.K.T.E. Society's Textile and Engineering Institute Ichalkaranji, affiliated to Shivaji University, Kolhapur is in partial fulfillment of degree B.Tech.(CSE). It is a bonafide report of the work carried out by us. The material contained in this report has not been submitted to any university or institution for the award of any degree. Further, we declare that we have not violated any of the provisions under the Copyright and Piracy / Cyber / IPR Act amended from time to time.

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We feel gratified to record our cordial thanks to other staff members of the Computer Science and Engineering Department for their support, help and assistance which they extended as and when required.

Thank you,

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ABSTRACT

The improper circulation of flow of blood inside the retinal vessel in the body is the primary source of most of the optical disorders including partial vision loss and blindness. Accurate blood vessel segmentation of the retinal image is used for biometric identification, computer-assisted laser surgical procedure, automatic screening, and diagnosis of eye diseases like diabetic retinopathy, age-related macular degeneration, hypertensive retinopathy, and so on. Proper identification of retinal blood vessels at its early stage helps medical experts to take convenient treatment procedures which could reduce vision loss. Automatic and proper retinal blood vessel segmentation helps to solve various optic diseases. As the number of patients and the necessity of the vessel segmentation is increasing day by day, an automated system is an alternative to the manual system. Retinal blood vessels have an important role in the diagnosis and treatment of various retinal diseases. For this reason, vasculature extraction is important in order to help specialists for the diagnosis and treatment of systemic diseases.

For segmentation various machine learning methods are available such as Support Vector Machines (SVM). But deep learning models perform better than traditional machine learning algorithms like SVM at segmentation tasks. Currently various deep learning models are available such as fully convolutional networks, encoder-decoder based models. U-Net and V-Net are two popular image segmentation architectures used in biomedical image segmentation. In an attempt to provide a highly accurate retinal blood vessel segmentation method, this project includes experiment with transfer learning approach. VGG- 19 is used as a pre-trained encoder for the U-Net model. The objective of the project is to study the impact of transfer learning on retinal blood vessel segmentation. The layers from the encoder section are frozen selectively in layer-by-layer manner. After each layer is frozen the model is trained and statistics are recorded. Using the recorded statistics, the impact of transfer learning is measured.

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1) Introduction:

In this era of technology, machine learning plays a vital role. In the last decade, everyone has seen how technology has transformed and made human life better. Technology enhances not only industrial efficiency of humans but also in day-to-day life of human health problems like detection of any problem or disease which has started growing in the human body.

The global health care sector continues to rise up to the new challenges presented by the current pandemic. With the development of medicine, more and more medical images need to be processed, and image processing technology has become more and more important. Traditional medical imaging image processing and analysis only depend on the doctor's experience, which not only wastes manpower but also affects the accuracy rate because the doctor's experience and physical condition affect judgment results. Therefore, the development of medical image processing technology has a very critical role in improving the efficiency of medical diagnosis.

In this world of emerging technology, this is a small contribution to segment retinal blood vessels present in retinal fundus image using deep learning model. Blood vessel segmentation images can help doctors in diagnosing multiple eye diseases. Segmenting blood vessels essentially and accurately is necessary for accurate analysis of main blood vessels and branches. Currently, doctors or physicians mark blood vessels manually according to experiences, which is characterized by low efficiency and easy interference by subjective factors. Therefore, the segmentation of retinal vessels is of important significance.

Within the past decade, deep learning has been increasingly utilized in the analysis of medical images. While the use of deep learning in computer vision has seen rapid growth in many different fields such as object detection, object classification, object segmentation, image style transfer, etc. The impact of transfer learning on object segmentation is going to be studied in this project.

a) Problem definition:

Development of transfer learning-based training of U-Net model for the segmentation of retinal fundus images using limited annotated dataset.

b) Aim and objective of project

Aim:

- To train a U-net model on a scarce dataset using weights from a pretrained model.
- To segment retinal blood vessels from retinal fundus images using a U-net model trained under scarce dataset.

Objectives:

Following are the objectives of proposed system:

1. To select appropriate source image domain and segmentation models.
2. To transfer the source model weights selectively, layer by layer to target the U-Net model.
3. To fine tune model training the model with a small subset of target real images (Retinal images from DRIVE dataset).
4. To evaluate the performance analysis showing the effectiveness of transfer learning for training the U-Net model using a small subset of real medical images (retinal images from DRIVE dataset)

c) Scope and limitation of the project:

Scope:

- This project can be used where availability of medical experts is limited and available dataset is also limited.
- This project can be useful for various applications in the medical sector such as blood clot detection. Diabetic retinopathy detection and also analyzing the blood vessels

Limitation:

- It is more difficult to identify the very small and thin vessels from background images. There are many problems like central light reflex, arbitrary branch crossing, contrast variation etc. in the vessel maps.
- In the medical field, the proper blood vessel segmentation is important as well as many times there is difficulty when analyzing the blood vessels in the fundus image. These problems are arising due to branching patterns, low quality of image resolution and bad contrast these problem in blood vessel segmentation

d) Timeline of the project:

Month	Task performed	Description
June	Project Domain selection and finalization. Selection of Problem Statement	Analyzed various project domains and finalized our project domain. Considered various problems related to that domain and selected one to resolve.
July	Literature Review	Study on various Research papers.
August	Synopsis Documentation	Documentation of synopsis and requirement Analysis
September / October	System Requirement. Module Identification and study	Identified the system requirements. Studied and identified the required modules in detail.
November	SRS Documentation and presentation	Created the Software Requirement Specification Document (SRS Document) and PowerPoint presentation
December January	Data Collection 100%.	30% coding done. Collection of the required data for code implementation. Testing and improvements in the required part. Analysis of limitations and drawbacks.
February	Data Collection. Coding 70%. Implementation70%. Testing and Improvements. Code update.	Collection of data in different formats due to change of approach.70% coding done according to updated approach. Implementation and Testing. Updating of code for meeting the desired requirements.
March	Coding 90%. Result analysis Project Report creation	90% coding done. Successfully tested and implemented.

e) Project Cost:

COCOMO RESULTS for Segmentaion using U-Net								
MODE	"A" variable	"B" variable	"C" variable	"D" variable	KLOC	EFFORT, (in person-months)	DURATION, (in months)	STAFFING, (recommended)
organic	2.4	1.05	2.5	0.38	0.500	1.159	2.644	0.438

Explanation: The coefficients are set according to the project mode selected on the previous page, (as per Boehm).
Note: the decimal separator is a period.

The final estimates are determined in the following manner:

effort = a*KLOC^b, in person-months, with KLOC = lines of code, (in thousands), and:

staffing = effort/duration

where a has been adjusted by the factors:

Hardware/Software cost:

Hardware/Software	Cost
Computer System with i5 11th generation or above	50000
NVIDIA 1080 TI GPU	10000
Python IDE to run machine Learning Modules	0
Dataset cost	0
Development cost	32000

2) Background study and literature overview

a) Literature Overview

Deep learning is a subset of machine learning which tries to mimic how the human brain works. The raw data is given to a deep learning network which itself identifies what features are relevant. Deep learning networks improve as you increase the amount of data used to train them. They need a huge amount of data to provide an optimal solution.

However, having huge amount of training data is not possible every time. Many times, while having a huge amount of data, it is not labeled. Which makes it useless for training deep learning models. Especially in the field of biomedical images, the label available is very limited. So, to overcome these problems some advanced methods in deep learning such as transfer learning and semi-supervised learning are present.

Transfer learning means transfer of knowledge from source task to target task, to compensate for lack of sufficient training data. After knowledge transfer, the pretrained model is further fine-tuned on target tasks. Abdelilah ADIBA et al. [3], highlights the impact of transfer learning for building segmentation using the U-Net model based on ResNet-34. They compared two models, where one model is pre-trained on ImageNet and the second one is randomly initialized. The results showed that pretrained models performed better by 17% compared to randomly initialized models. Paper also suggests adapting recent approaches such as Generative Adversarial Networks for better results and more accuracy.

Olaf Ronneberger et al. [1], proposed a deep learning model for image segmentation. The architecture consists of a contracting path to capture context and a symmetric extending path that enables precise localization. This method outperforms the prior best method, a sliding-window convolutional network on ISBI challenge for segmentation of neuronal structures in electron microscopic tasks. This method performs segmentation of 512*512 images in less than a second on a modern GPU. As this model performs better in biomedical image segmentation than other prior models, the U-Net model is chosen in this project to perform retinal vessel segmentation.

Jason Yosinski et al. [2]. Proposed research paper on quantifying the generality versus specificity of neurons in each layer of a deep convolutional neural network. It describes that Transferability is negatively affected by two distinct issues:

(1) the specialization of higher layer neurons to their original task at the expense of performance on the available target task, which was expected, and
(2) optimization difficulties present in related to splitting networks between co-adapted neurons, which was not expected.

Paper also documents that the transferability of features decreases as the distance between the base task and target task increases, but that transferring features even from distant tasks can be better than using random features. A final amaze result is that initializing a network with transferred features from almost any number of layers can produce a boost to generalization that lingers even after fine-tuning to the target dataset.

Davood Karimi et al. [4]. The experiments performed show that although transfer learning reduces the training time on the target task, the improvement in segmentation accuracy is highly task/data dependent. It is observed that convolutional filters of an FCN change little during training for medical image segmentation, and still look random at convergence. Then further show that quite accurate FCNs can be built by freezing the encoder section of the network at random values and only training the decoder section.

Zhexin Jiang et al. [6], proposed a supervised method based on a pre-trained fully convolutional network through transfer learning. The proposed supervised learning method uses fully convolutional AlexNet for retinal vessel segmentation. This method also includes data augmentation to increase the amount of training data. After the segmentation post processing is done to slightly increase the accuracy and look nicer. This method does regional segmentation of the retinal vessel and binds the result at the end to produce desired result. This method verifies that models pre-trained from different medical domains or even natural image dataset can be used for the task.

b) Investigation of current project and related work:

We started our project with an aim to “Study impact of transfer learning on retinal vessel segmentation using U-Net model”. This means that we have to transfer weights from a pretrained model to our U-Net model. Another challenge is to train models on a very scarce dataset consisting of only 20 images. So, to transfer weights of pretrained models, VGG- 19 trained on ImageNet dataset is chosen.

U-Net model proposed by Olaf Ronneberger et al. [1] outperforms prior best methods. Therefore, to segment retinal blood vessels U-Net model is chosen. Also, Davood Karimi et al. [4] states that accurate FCNs can be built by freezing encoder section of the network and only training decoder section.

The whole system was designed based on the principle of transfer learning. For this we have created 7 different models out of which one model’s weights are randomly initialized and all other models have pretrained weights. This project includes training all the models on the DRIVE dataset and recording the statistics and analyzing the behavior of models in the training and testing phase.

3) Requirement analysis

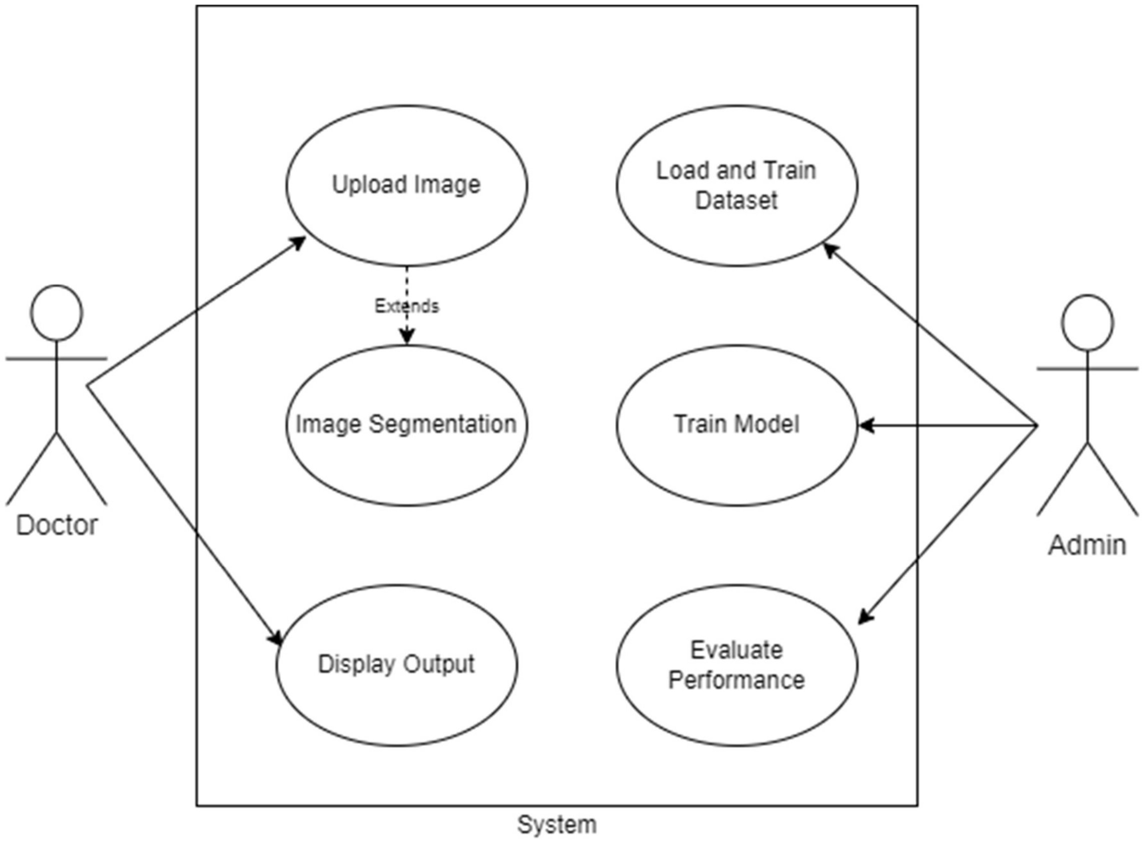
a) Requirement Specification:

1. Use a deep learning model to carry out segmentation.
2. Train model with limited training dataset.
3. Segment retinal vessels with very high accuracy.
4. Model must be able to reduce overfitting

b) User stories:

- As a doctor I want to segment retinal blood vessels so that I can detect Diabetic retinopathy
- As a Doctor I want to segment retinal blood vessels so that I can detect Glaucoma
- As a Doctor I want to segment retinal blood vessels so that I can detect Age related macular degeneration
- As a doctor I want to segment retinal blood vessels so that I can detect Hypertension and stroke induced changes

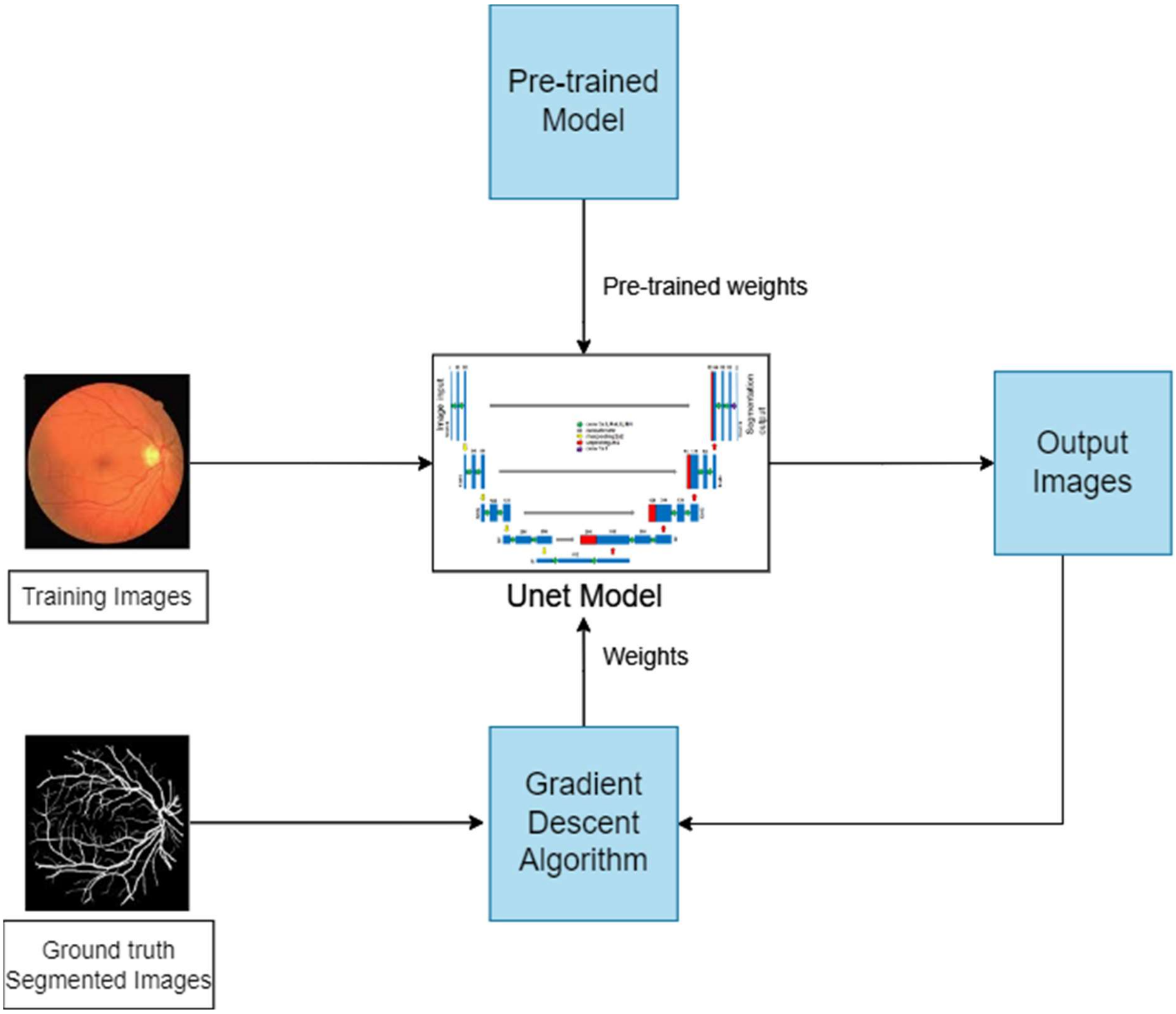
c) Use case Diagram:



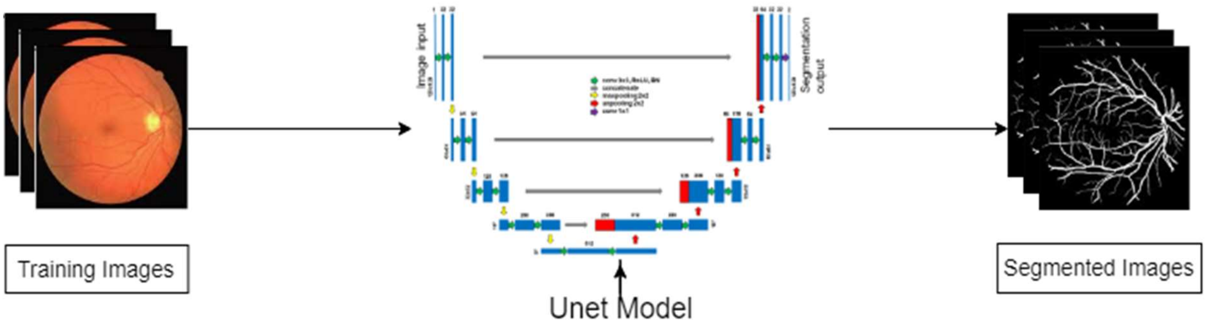
4) System Design:

a) Architecture Design:

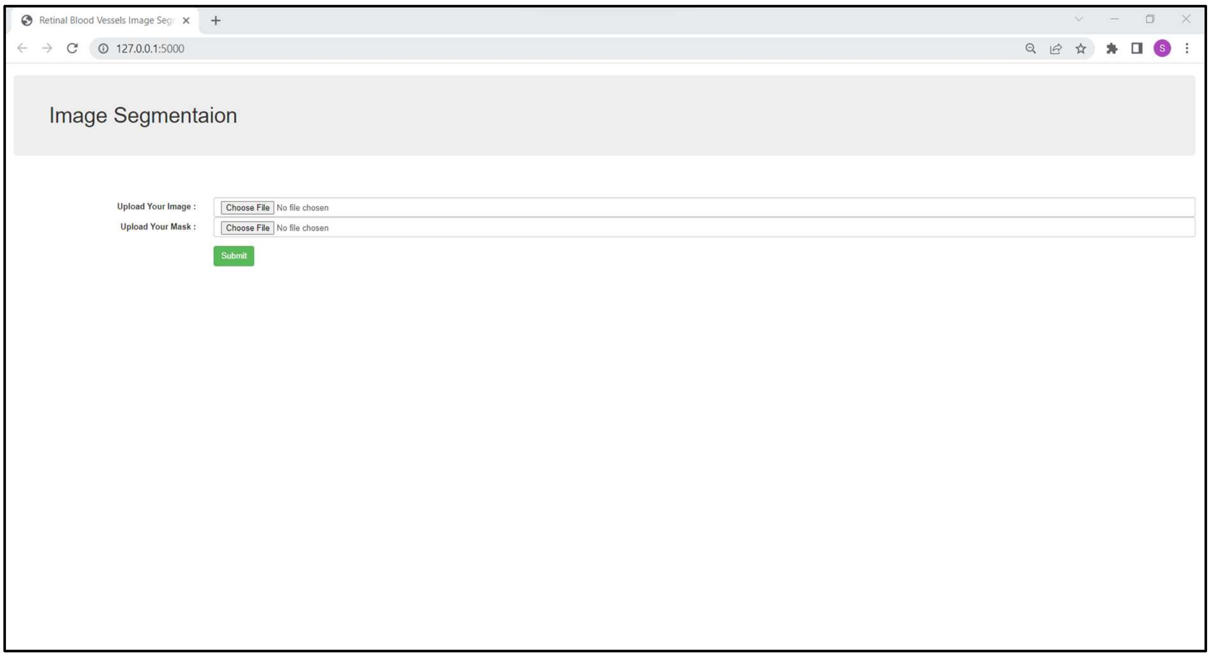
Training:



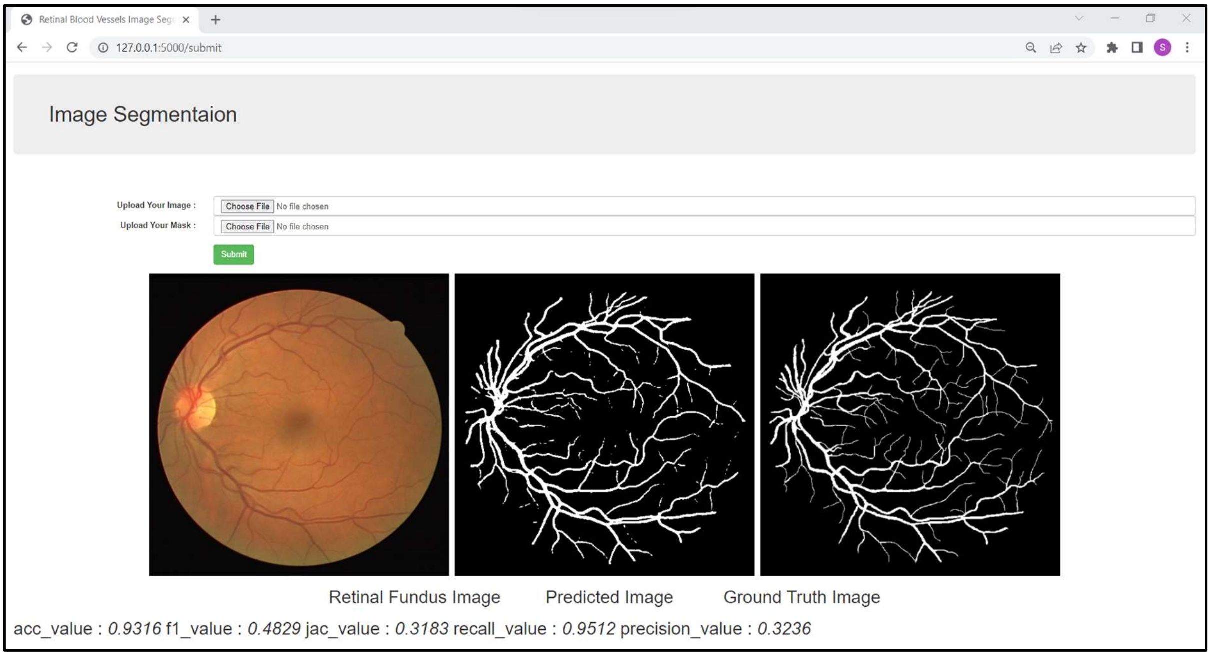
Testing:



b) User Interface Design:



In this interface to get segmented image, upload image under Upload your Image section and upload mask under mask section (to compare model result with actual result) and click submit.



After clicking submit, Retinal Fundus Image, Predicted Image and Ground truth image will be shown along with accuracy value, jackcard value, recall and precision.

c) Algorithmic Description of each module:

1. Image Augmentation:

In this, Image Augmentation is used for resizing the image. When you resize an image and do not resample it, you change the image's size without changing the amount of data in that image. After resizing the image, the image size is converted into 512 x 512. Total number of images is 20. 20 images of retinal blood vessels and 20 masks for each image in retinal blood vessels.

2. Weight transfer:

The main reason is that instead of making a new required model and starting to train it from the start, we can use a trained model and change necessary parameters to get the desired answer. If we take an available pre-built model, it will have weights that are actually trained for a task, and not just random numbers. Hence, we will be able to easily manipulate them to perform our desired work.

We have used the VGG- 19 pretrained model for the encoder part of the model. The VGG- 19 model is pretrained on ImageNet dataset. The architecture of VGG- 19 is matched with the U-Net's encoder part. The encoder architecture follows 2 conv2d blocks in a max pooling and a skip connection in each layer. The encoder architecture contains 4 layers each with output feature matrix size of 512 x 512,256 x 256, 128 x 128, 64 x 64.

3. U-net model

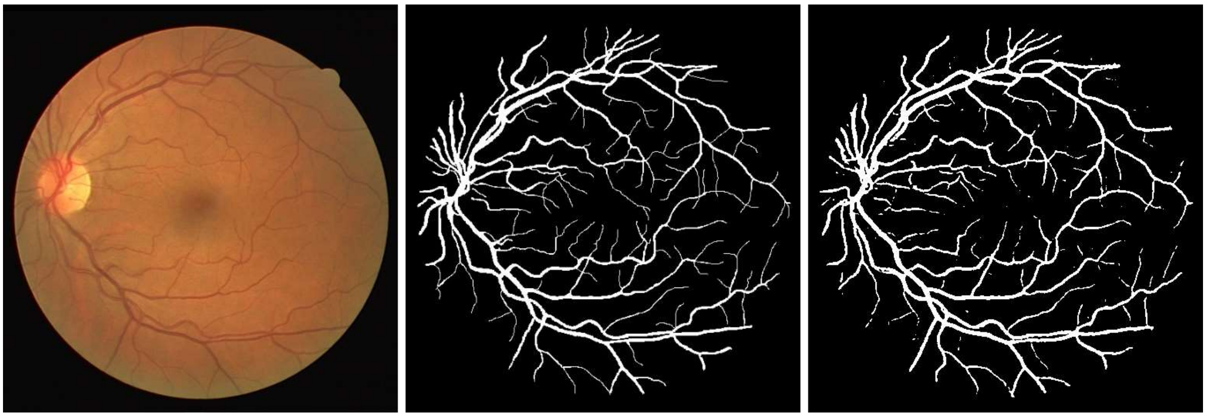
The U-net architecture is an end-to-end network built upon the Fully Convolutional Network, composed from encoder and decoder parts with skip connections, in order to get a precise segmentation and to localize high resolution features, these connections concatenate the input of each encoding stage input with its facing decoding stage input. The encoder part of the model extracts features via several convolutions and ReLU activations to get the compressed features, then decompresses the features through the available decoder part which contains deconvolutions and ReLU activations.

4. Training module:

The model was trained for 100 epochs. Input image size was 512 x 512 pixels and total number of images were 20 images. The training was done on NVIDIA TitanX GPU. The average time for each epoch to train was 6 seconds and that for to complete 100 epochs was 10 minutes. For first 15 epochs the precision was below 0.90 but after 15 epochs precision went up 0.90.

5. Testing module:

Testing was done on 20 images of the DRIVE dataset. The images were first resized to 512 x 512-pixel size and passed to pretrained U-Net model. The output produced by the model was compared with ground truth image and based on that accuracy, recall and precision was calculated.



a) Input Image b) Ground truth image c) Output Image

Result produced by testing module

5) Implementation:

a) Environment Setting for running the project:

For running the project, a python environment is necessary.
The libraries required to be installed are as follows:

1) TensorFlow
2) Keras
3) OpencvThe command that can be used to install these libraries ispip install<library_name>

The other internal libraries that are needed are:

4) NumPy
5) Pandas
6) Glob
7) Tqdm
8) Sklearn.metrics
9) Imageio
10) Os
11) from tensorflow.keras.layers import Conv2D, BatchNormalization, Activation, Conv2DTranspose,MaxPool2D, concatenate, input.
12) from tensorflow.keras.models import Model
13) from tensorflow.keras.applications import VGG- 19

b) Detailed description of methods:

1. Build VGG- 19 U-Net:

   VGG- 19 is a convolutional neural network (CNN) that is 19 layers deep. You can load a pre-trained version of the network trained on more than a million images from the available ImageNet database. The available pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned high feature representations for a wide range of images.

   The U-Net architecture contains two paths. First path is the encoder, which is used to capture the context in the image. The encoder consists of max pooling and convolutional layers. The second path is the decoder, which precisely localizes required features using transposed convolutions. Hence it is an end-to-end fully convolutional network

1.1 Convolution operation

There are two inputs to a convolutional operation. An input image of size (512 x 512 pixels) and set of 'k' filters also called kernels or feature extractors. The output of a convolutional operation is a feature map.

1.2 Max pooling operation:

The function of pooling is to reduce the size of the feature map so that we have fewer parameters in the network. Basically, from every 2x2 block of the input feature map, we select the maximum pixel value and thus obtain a pooled feature map. The size of the filter and strides are two important hyper-parameters in the max pooling operation. The idea is to retain only the important features (max valued pixels) from each region and remove the information which is not important.

1.3 Transposed Convolution:

Transposed convolution is deconvolution is a technique to perform up sampling of an image with learnable parameters. Transposed convolution is exactly the opposite process of a normal convolution, the input volume is a low-resolution image and the output volume is a high-resolution image.

In this method we have used the VGG- 19 pertained model as an encoder part of the U-Net model.

2. **Save results:**

   Input Image, ground truth image and predicted image are concatenated together to create a single image. Generated image is stored in results directory for future reference.

3. **dice coefficient**

   This method is used to calculate dice coefficient to compute dice loss. Dice loss is used for model training.
   Dice coefficient is given by,
   Dice coefficient = (2*precision * recall) / precision + recall.
   Dice loss is calculated as,
   Dice loss = 1 - Dice coefficient.

4. **model fit**

   This method is used for training our deep learning model used for segmentation of images. Parameters like number of epochs, training dataset, callbacks are passed to fit method.

5. **Augment data**

This method is used for general preprocessing of the images such as image reshape or changing the format of the image. This is an important part before passing the image to model.

c) Implementation Details:

1. Implementation of Build VGG- 19 U-Net

   In this method, the first pretrained VGG- 19 model trained on ImageNet dataset excluding top is loaded. Then the encoder part of the U-Net model is replaced by VGG-19 layers, the decoder part of the U-Net model is concatenated with VGG- 19. Batch normalization is added after each ReLU activation as regularization.

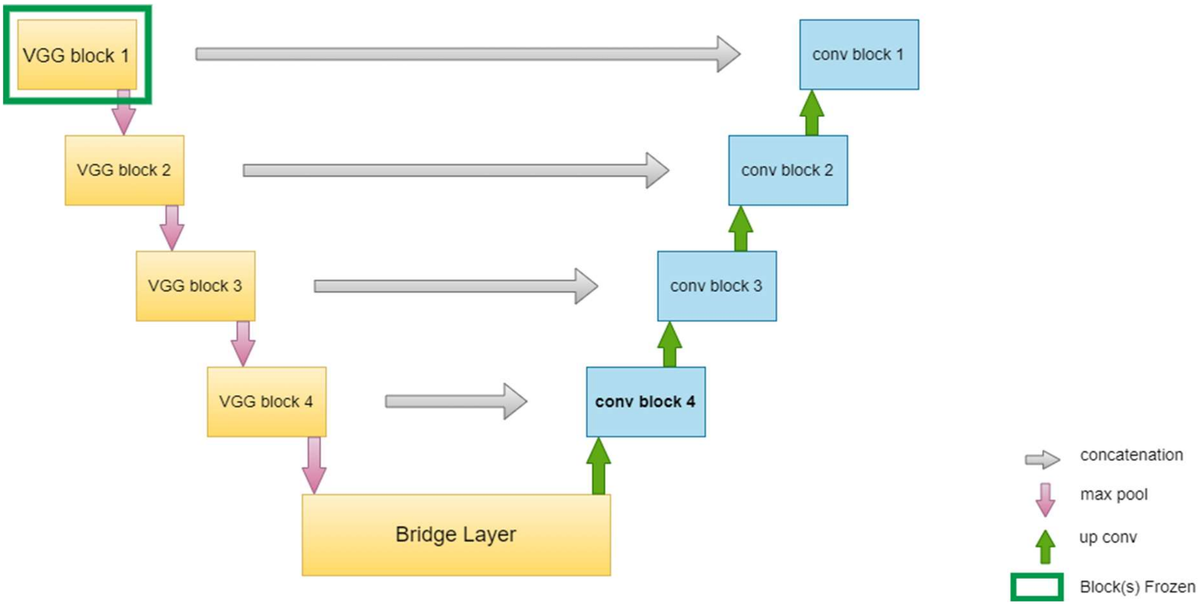
2. Weight Transfer Module:

   This module is used to transfer weights of pretrained models (VGG- 19) to the encoder section of the U-Net model. To study the impact of transfer learning, layers are frozen in one-by-one manner. That is seven different models are created for experimentation.

Description of each required model is as follows:

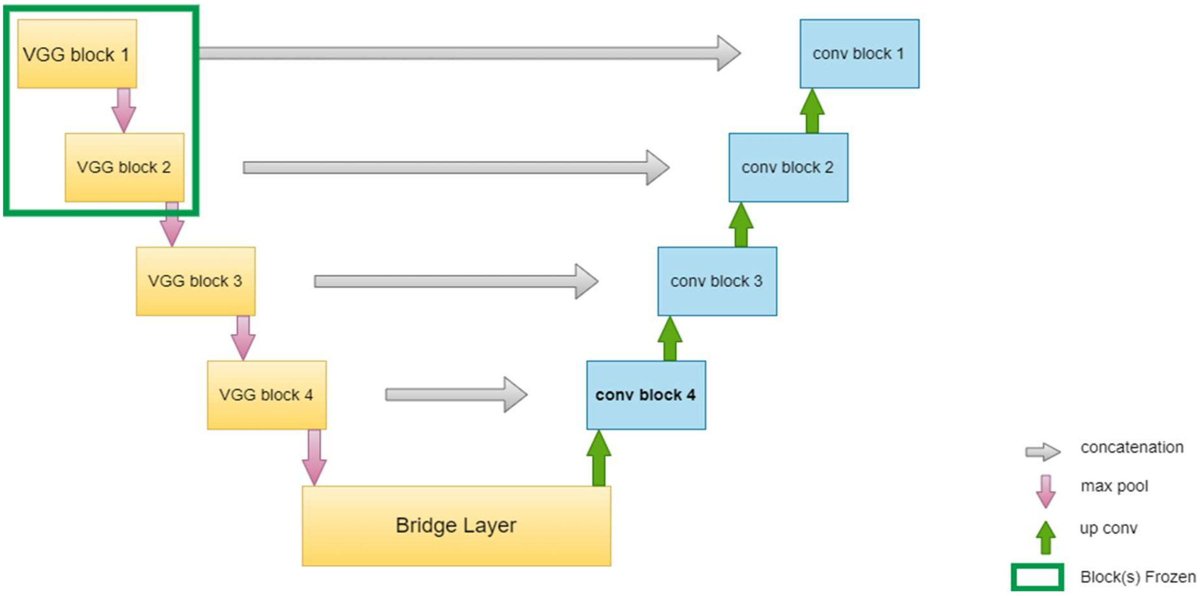
Model Name	Model Description	Model Weights
Pretrained VGG- 19 M1	First block is frozen and remaining layers kept trainable	Pretrained weights
Pretrained VGG- 19 M2	Two blocks are frozen and remaining layers kept trainable	Pretrained weights
Pretrained VGG- 19 M3	Three blocks are frozen and remaining layers kept trainable	Pretrained weights
Pretrained VGG- 19 M4	Four blocks are frozen and remaining layers kept trainable	Pretrained weights
Pretrained VGG- 19 M5	Five blocks are frozen and remaining layers kept trainable	Pretrained weights
Pretrained VGG- 19	All layers kept trainable	Pretrained weights
U-Net Model	All layers kept trainable	Random Initialization

Pretrained VGG- 19 M1:



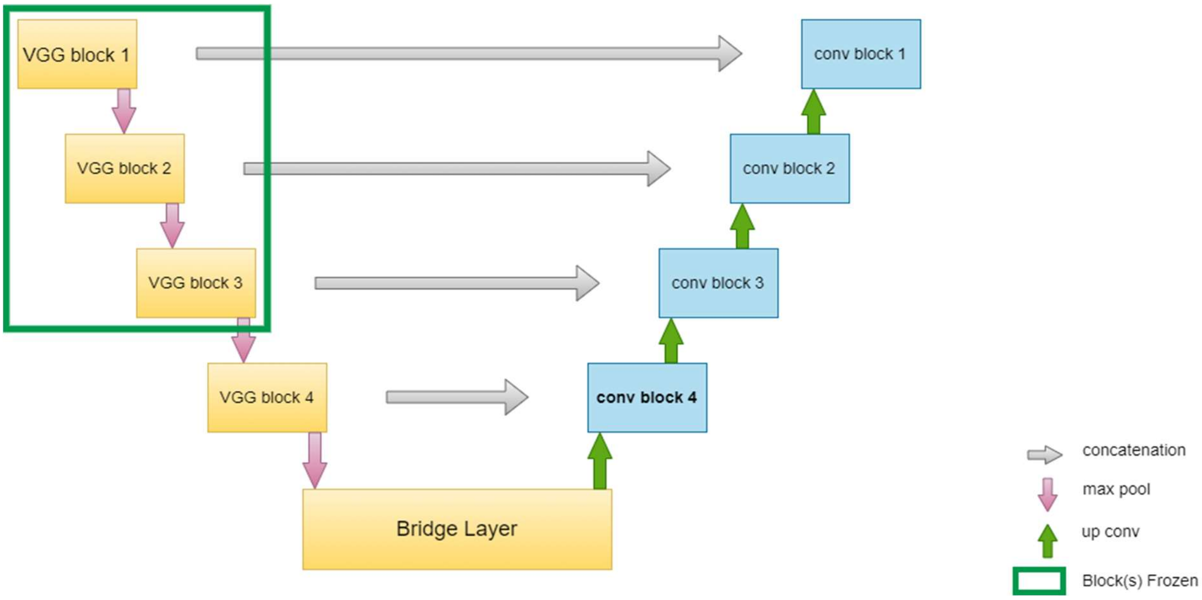
The yellow blocks in the above figure represent encoder blocks and blue blocks represent decoder blocks. In this first block is kept frozen and the remaining blocks including all remaining encoder blocks, bridge layer, and all decoder blocks kept trainable, and trained for 100 epochs the training precision was 99.71 percent.

Pretrained VGG- 19 M2:



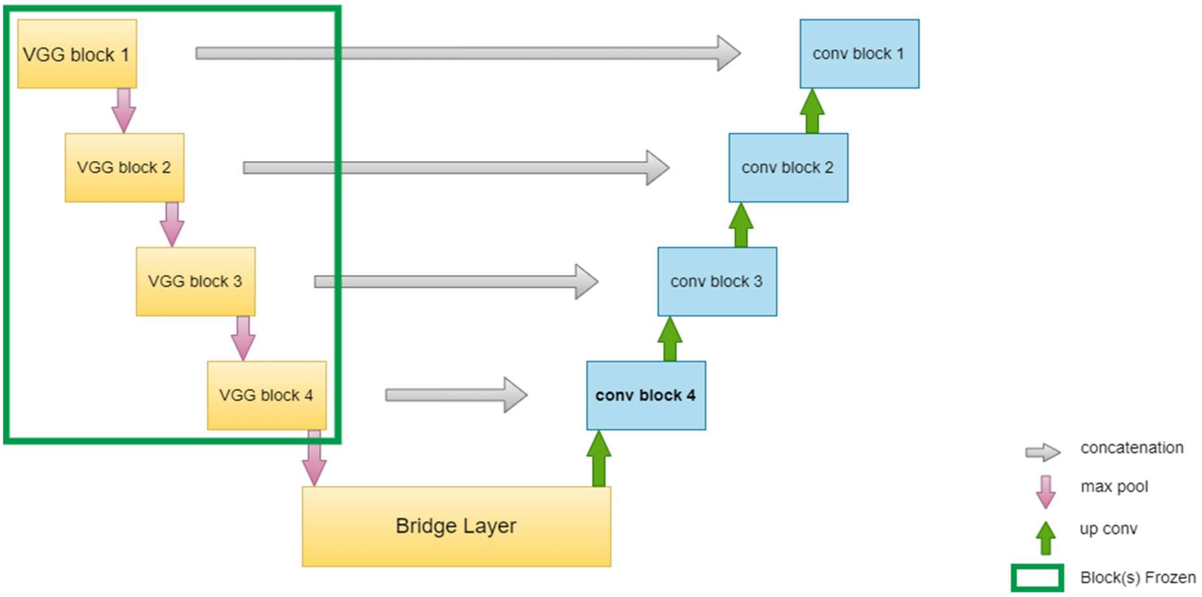
The yellow blocks in the above figure represent encoder blocks and blue blocks represent decoder blocks. In this first and second block is kept frozen and the remaining blocks including all remaining encoder blocks, bridge layer, and all decoder blocks kept trainable, and trained for 100 epochs the training precision was 99.64.

Pretrained VGG- 19 M3:



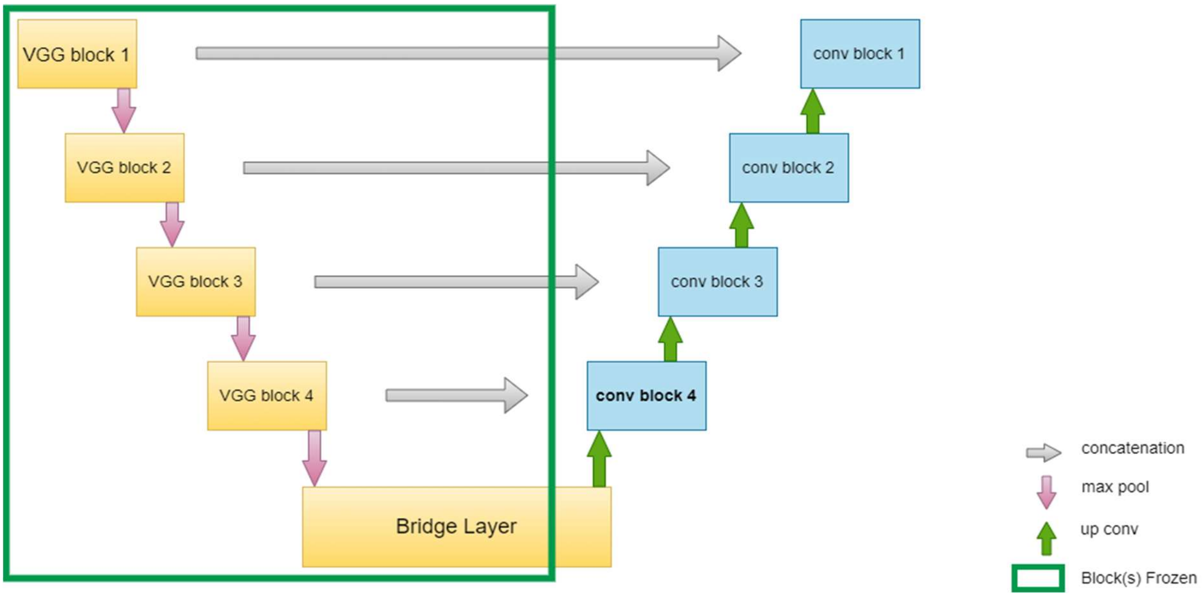
The yellow blocks in the above figure represent encoder blocks and blue blocks represent decoder blocks. In this first three blocks are kept frozen and the remaining blocks including all remaining encoder blocks, bridge layer, and all decoder blocks kept trainable, and trained for 100 epochs the training precision was 98.48 percent.

Pretrained VGG- 19 M4:



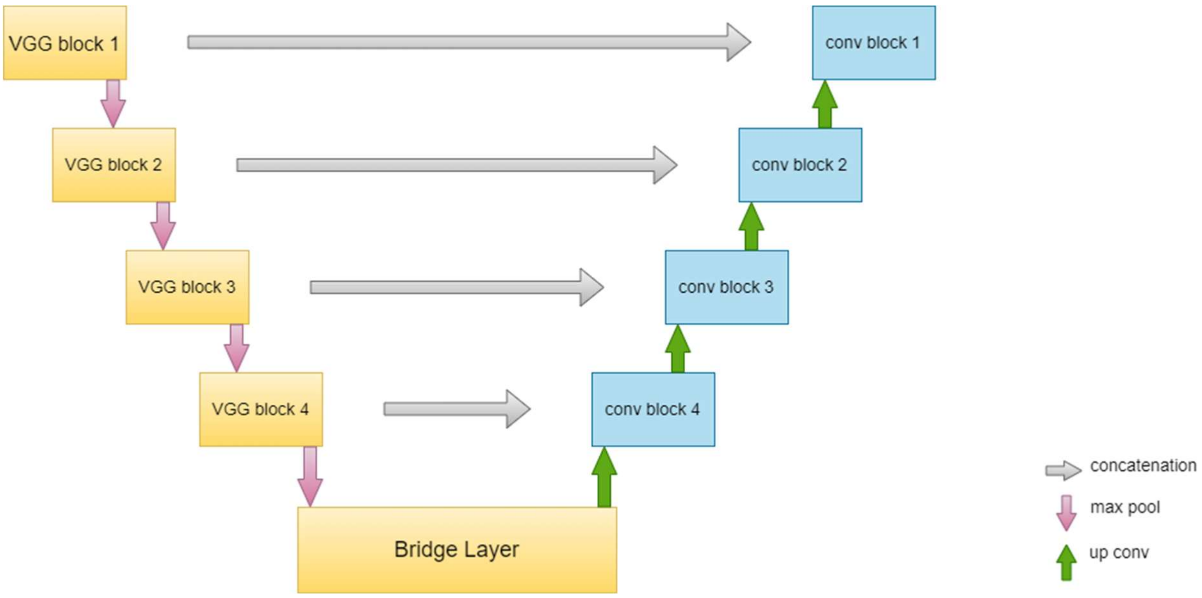
The yellow blocks in the above figure represent encoder blocks and blue blocks represent decoder blocks. In this first four blocks are kept frozen and the remaining blocks including all remaining encoder blocks, bridge layer, and all decoder blocks kept trainable, and trained for 100 epochs the training precision was 99.36 percent.

Pretrained VGG- 19 M5:



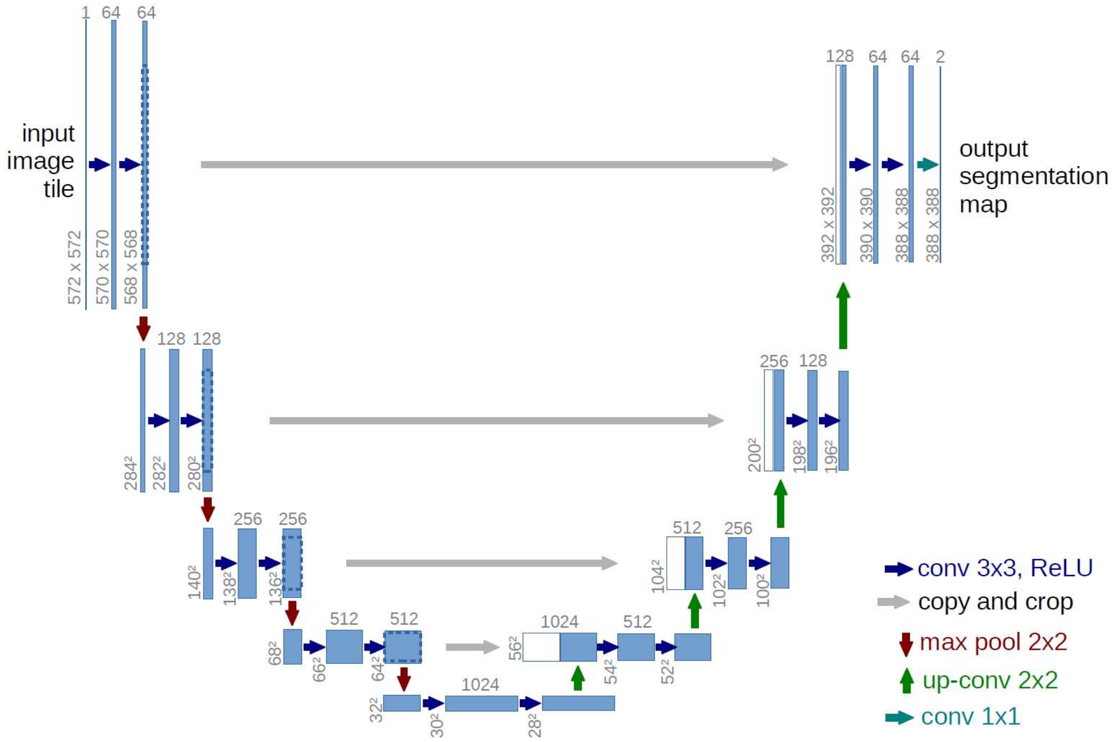
The yellow blocks in the above figure represent encoder blocks and blue blocks represent decoder blocks. In this first four and bridge layer kept frozen and the remaining blocks including all remaining encoder blocks and all decoder blocks kept trainable, and trained for 100 epochs the training precision was 99.30 percent.

Pretrained VGG-19:



The yellow blocks in the above figure represent encoder blocks and blue blocks represent decoder blocks. In this all encoder and decoder blocks are kept trainable and trained for 100 epochs the training precision was 99.71 percent. Note that the pretrained weights are present before training instead of random weights.

U-Net Model:



In this model U-Net architecture is matched with remaining pretrained models. In this all encoder and decoder blocks are kept trainable. The initial weights taken for training are random in this case. The model trained for 100 epochs; the training precision was 99.71 percent.

6) Integration and Testing

a) Description Of integration module

Output of module				Input of module			
Sr. No.	**Module**	**Output**	**Type**	**Module**	**Input**	**Type**	**Status**
1.	Image Augmentation	Image of size 512*512	Image	U-Net Model	Image generated from image augmentation	Image	Verified
2.	Weight Transfer	Matrix of weights	Float	U-Net Model	Weight Matrix	Float	Verified
3.	U-Net Model	Segmented Image	Image	Training Module	Segmented and ground truth image	Image	Verified
4.	U-Net Model	Segmented Image	Image	Testing Module	Segmented Image	Image	Verified

b) Testing

Sr. No.	Test Case Title	Description	Expected Outcome
1.	Successful image Input	The segmentation system is successful if it gets retinal fundus image as input	Retinal fundus image input must be successful.
2.	Unsuccessful input attempt.	Wrong input image, such as images other than retinal fundus.	Prompt "*wrong Input error*" and ask for input again.
3.	Successful blood vessel segmentation process	The retinal segmentation process is successful when an appropriate binary mask representing blood vessels is generated.	The retinal segmentation process must be successful.

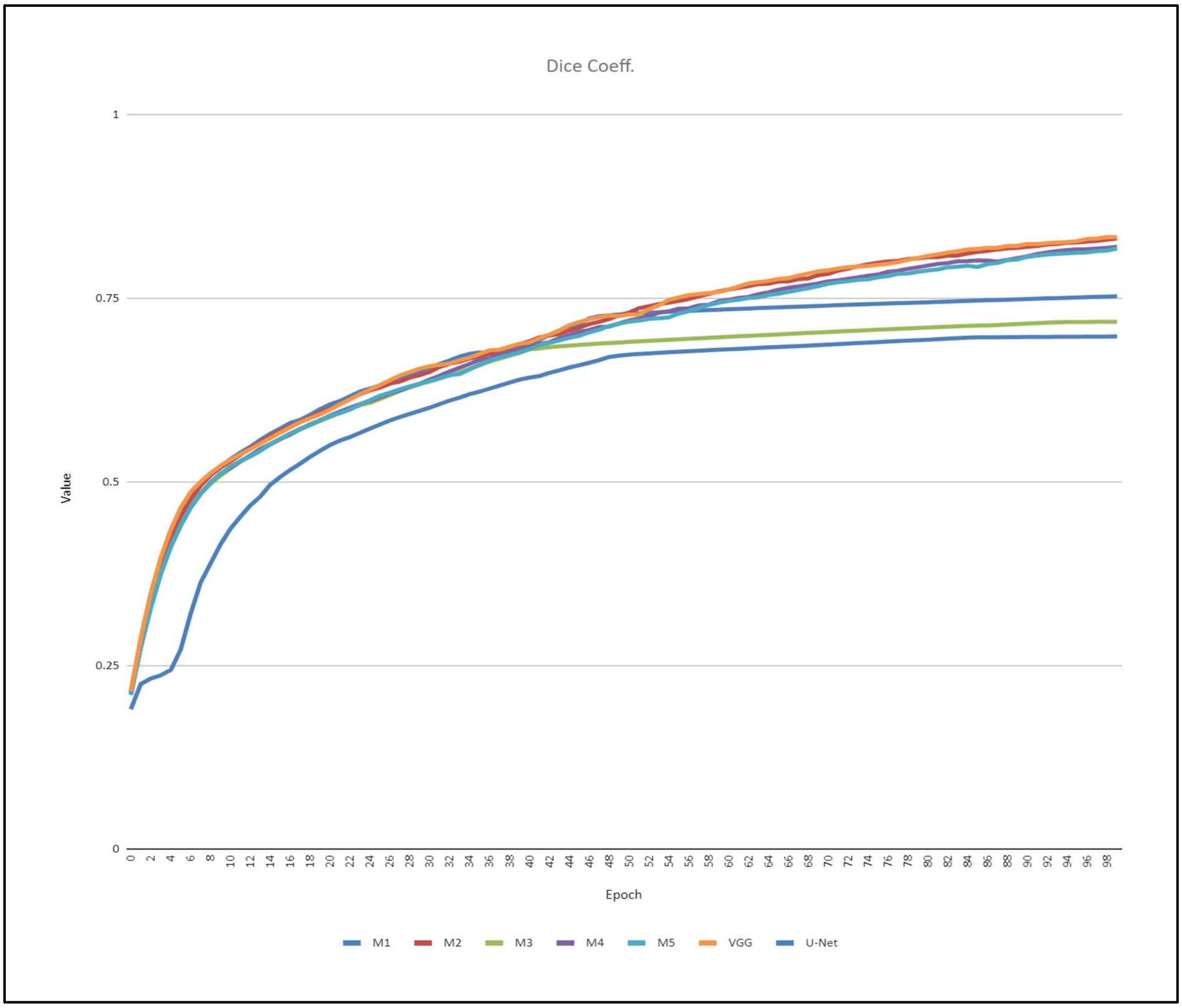
7) Performance Analysis:

Metrics Used:

1. **Dice coefficient: -**

Dice Coefficient is 2 * the Area of Overlap divided by the total number of pixels in both images.

The Dice coefficient is very similar to the IoU. They are positively correlated. Like the IoU, they both range from 0 to 1, with 1 signifying the greatest similarity between predicted and truth.



Graph Description:

The given graph represents the value of Dice Coefficient over the training phase of 100 epochs. X-axis represents epoch value whereas Y-axis represents value of dice coefficient. At the 0th epoch itself the dice coefficient value is higher for pretrained models. Over the training period the green line representing model M3 performed poor compared to other models. That means if features in the 3rd block of the model are not quite similar to our domain.

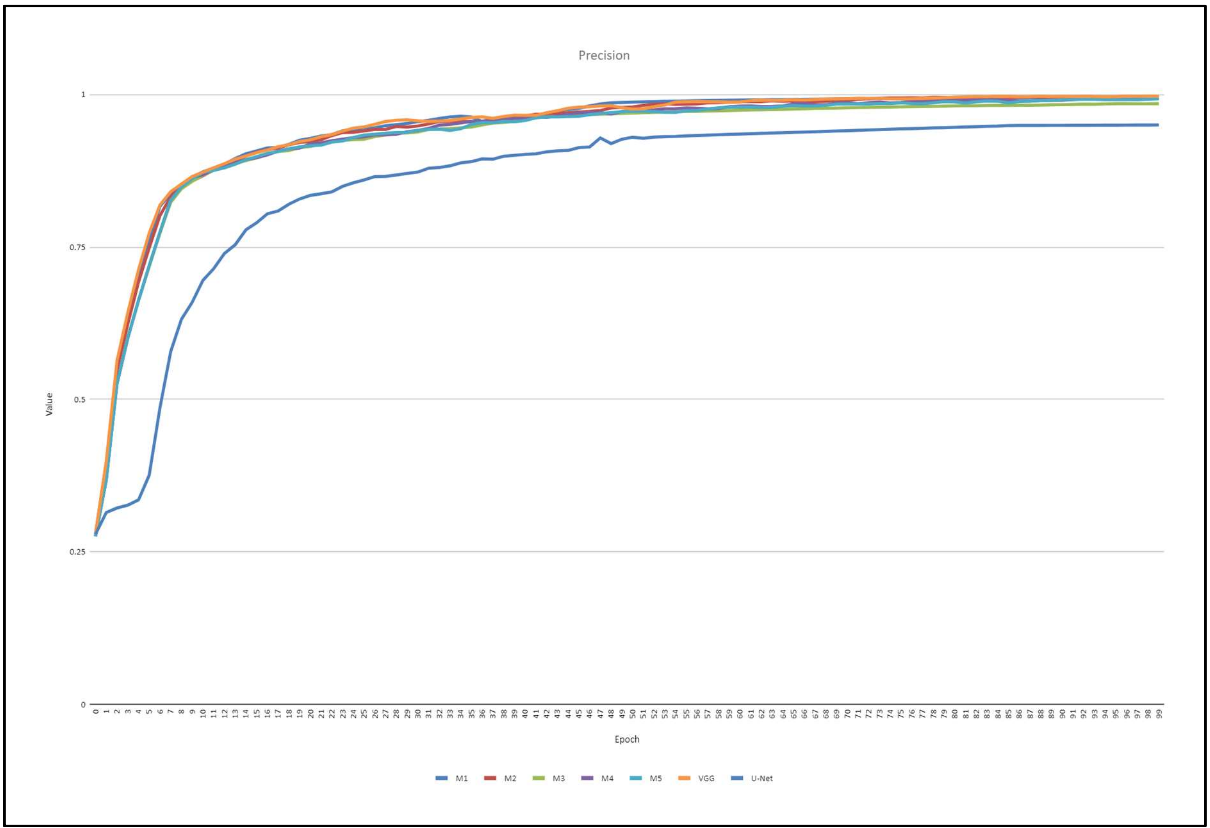
2. **Precision: -**

Precision effectively describes the purity of our positive detections relative to the ground truth. Of all of the objects that we predicted in a given image, how many of those objects actually had a matching ground truth annotation?

Or

Precision is the proportion of boundary pixels in the automatic segmentation that correspond to boundary pixels in the ground truth.

Precision can be seen as a measure of quality, and recall as a measure of quantity.



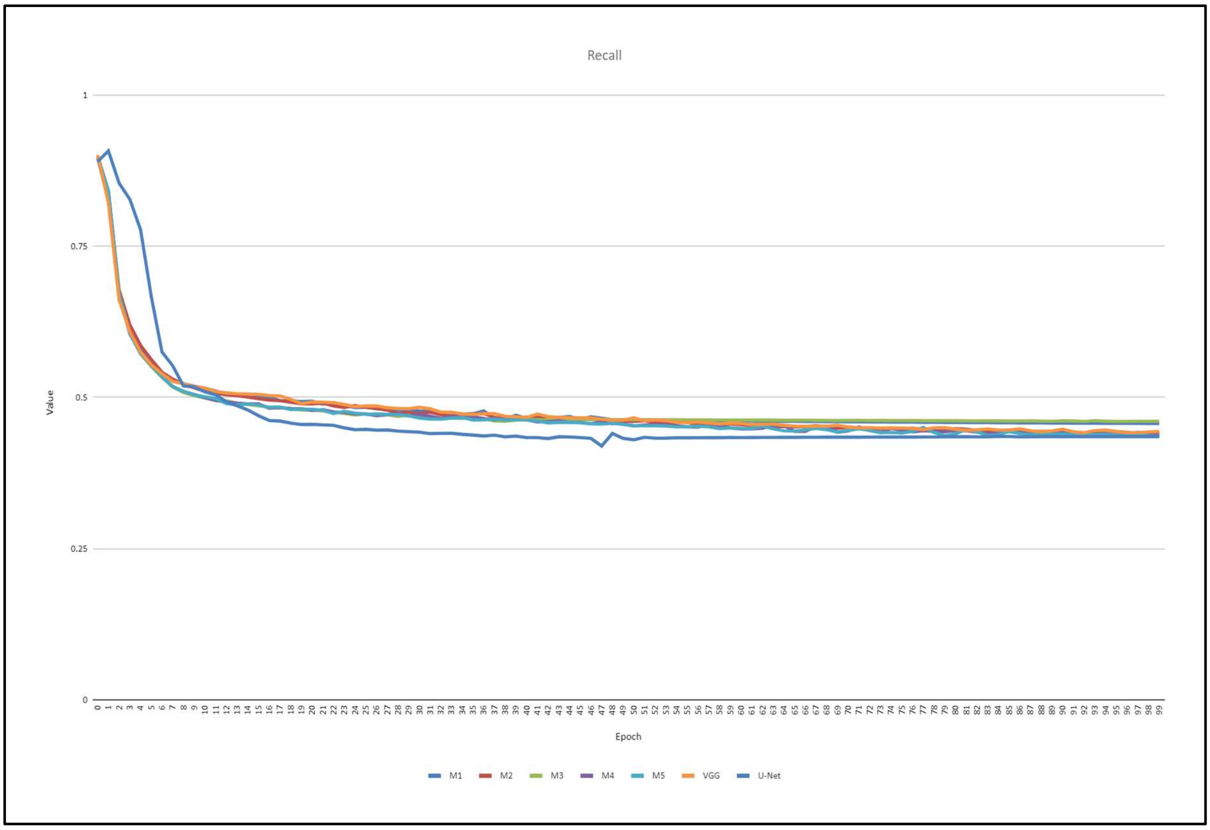
Graph Description:

The given graph represents the value of precision over the training phase of 100 epochs. X-axis represents epoch value whereas Y-axis represents value of precision. Within few epochs precision value of pretrained models overtake U-Net model with random weights. Over the training period the blue line representing U-Net model performed poor compared to other models. That means model with pre-trained weights have higher precision value over model with random weights (U-Net Model in this case).

3. **Recall:**

Recall is defined as the proportion of boundary pixels in the ground truth that were successfully detected by the automatic segmentation.

Recall also gives a measure of how accurately our model is able to identify the relevant data.



Graph Description:

The given graph represents the value of recall over the training phase of 100 epochs. X-axis represents epoch value whereas Y-axis represents value of recall. In the initial phase U-Net model has slightly higher value. But after around 12-13 epochs blue line representing U-Net model performed poor compared to other models. That means model with pre-trained weights have higher recall value over model with random weights (U-Net Model in this case).

8) Future scope:

The technique which is used in this project is very useful when there is a small dataset present. When high accuracy is required but the availability of the dataset required for that model training is less then this method is useful. Transfer learning can play a vital role when there is less dataset present. The DRIVE dataset is used in this project, but the problem is there are very few images present to train the model. This project implementation can be used for various disease detection such as lung cancer and brain tumor.

In the future work, research can be extended to develop an automated segmentation system for other problems such as MR brain images. Different object detection in optical images, such as hemorrhage, exudates, optic disc, cotton wool spots, and artery-venous classification, measurement of tortuosity, vessel width, and branching angle. It can also be examined for the disease of Alzheimer's and Amyotrophic Lateral Sclerosis (ALS). But to investigate, researchers need to collect required clinical datasets first.

9) Applications:

1. Diabetic retinopathy:

Diabetic retinopathy (DR) is also called as diabetic eye disease, which causes the damage to the retina due to diabetes mellitus and that leads to blindness when the disease reaches the extreme stage. The medical tests take a lot of procedure, money, and time to test for the proliferative stage of diabetic retinopathy (PDR). Hence to solve this problem, the model is proposed to detect and identify the various stages of diabetic retinopathy which is also identified by its main feature that is neovascularization.

In the proposed system, this aims to correctly identify the presence of neovascularization using color fundus images which are available. The presence of neovascularization in an eye is an indication that the eye is affected with proliferative PDR disease. Neovascularization is the development of new abnormal blood vessels in the retina from normal. Since the occurrence of neovascularization may lead to partial or complete vision loss in person, timely and accurate prediction is important in this case.

2. Glaucoma:

Glaucoma is a neuro-degenerative eye disease developed due to an increase in the Intraocular Pressure inside the retina. This being the second largest cause of blindness worldwide, it can lead the person towards complete blindness if an early diagnosis does not take place in this disease. With respect to this underlying issue, there is a huge need of developing a system that can effectively work in the absence of excessive equipment, skilled medical practitioners and also is less time consuming.

3. Age related macular degeneration:

Age-related macular degeneration (AMD) is an eye disease that can blur your central vision of the eye. It happens when aging causes damage to the macula in the eye. the part of the human eye that controls sharp, straight-ahead vision. The macula is part of the eye retina (the light-sensitive tissue at the back of the eye).

AMD is a common condition as it's a leading cause of vision loss for older adults. AMD doesn’t cause complete blindness, but losing your central vision can make it harder to see faces, drive, read or do close-up work like cooking or fixing things around the house.

AMD happens very slowly in some young people and faster in others. If you have seen early AMD, you may not notice the vision loss for a long time. That’s why it’s important to get regular eye exams or checkup to find out if you have AMD.

4. Hypertension and stroke induced:

High blood pressure means the force of the blood in vessels pushing against the blood vessel walls is consistently in the high range. Uncontrolled high blood pressure can lead to stroke, heart failure, heart attack or kidney failure in humans. Two numbers are represented in blood pressure. The higher (systolic) number is the pressure in our arteries when our heart beats. The lower (diastolic) number is the pressure while our heart rests between beats. The systolic number is always listed first. Blood pressure is measured in millimeters of mercury (mm Hg) unit. Normal blood pressure in humans is below 120/80 mm Hg. If you're an adult and your systolic blood pressure is 120 to 129, and your diastolic blood pressure is less than 80, you have elevated blood pressure. High blood pressure for humans is a systolic pressure of 130 or higher or a diastolic pressure of 80 or higher that stays high over time.

10) Installation Guide and User Manual:

Environment Setting for running the project:

The command that can be used to install these libraries is
pip install <library_name>

For running the project, a python environment is necessary.

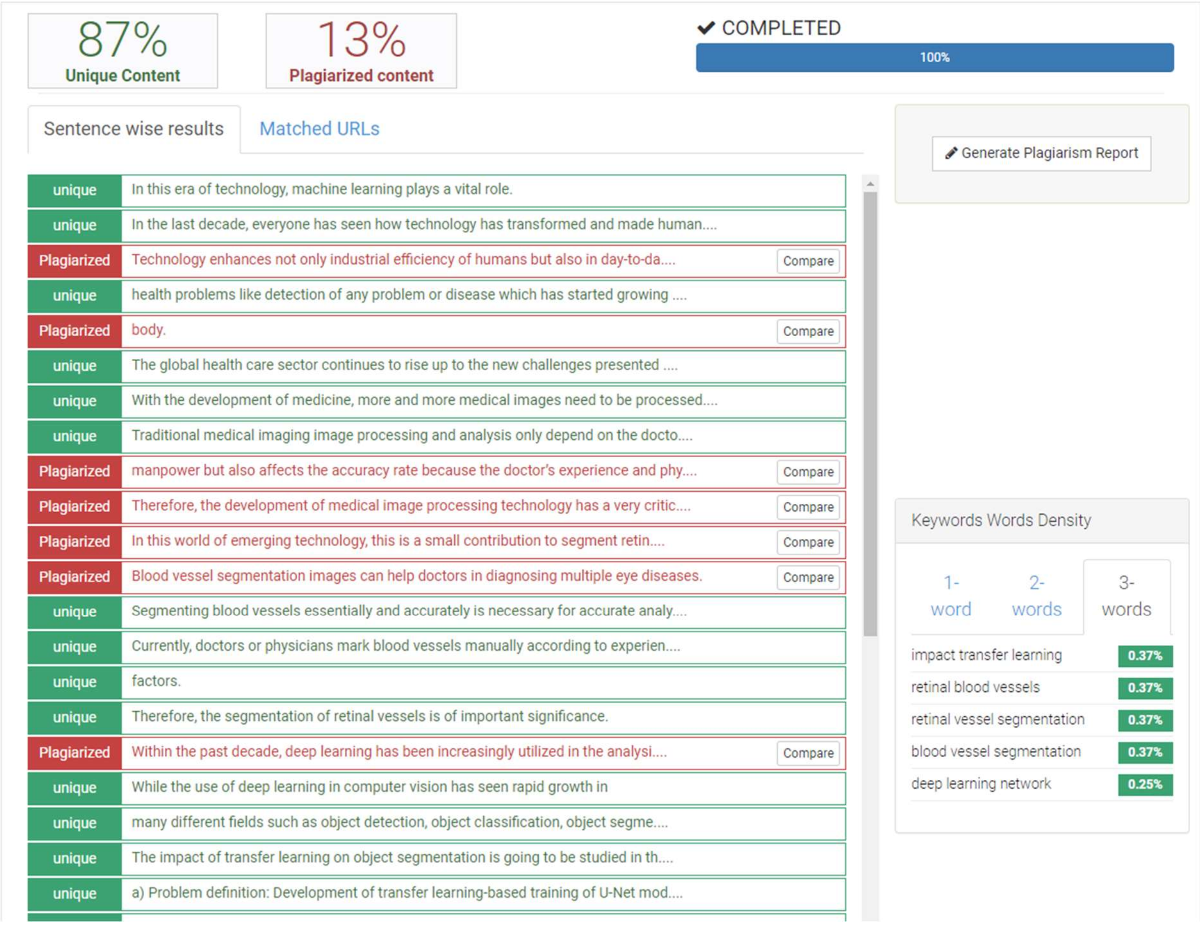
The libraries required to be installed are as follows:

1. TensorFlow
2. keras
3. Opencv
4. flask

The other internal libraries that are needed are:

1. NumPy
2. Pandas
3. Glob
4. Tqdm
5. Sklearn.metrics
6. Imageio
7. Os

11) Plagiarism Report:


87%
Unique Content
13%
Plagiarized content
COMPLETED
100%
Sentence wise results
Matched URLs
Generate Plagiarism Report
unique
In this era of technology, machine learning plays a vital role.
unique
In the last decade, everyone has seen how technology has transformed and made human....
Plagiarized
Technology enhances not only industrial efficiency of humans but also in day-to-da....
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unique
health problems like detection of any problem or disease which has started growing ....
Plagiarized
body.
Compare
unique
The global health care sector continues to rise up to the new challenges presented ....
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With the development of medicine, more and more medical images need to be processed....
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Traditional medical imaging image processing and analysis only depend on the docto....
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manpower but also affects the accuracy rate because the doctor's experience and phy....
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Plagiarized
Therefore, the development of medical image processing technology has a very critic....
Compare
Plagiarized
In this world of emerging technology, this is a small contribution to segment retin....
Compare
Plagiarized
Blood vessel segmentation images can help doctors in diagnosing multiple eye diseases.
Compare
unique
Segmenting blood vessels essentially and accurately is necessary for accurate analy....
unique
Currently, doctors or physicians mark blood vessels manually according to experien....
unique
factors.
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Therefore, the segmentation of retinal vessels is of important significance.
Plagiarized
Within the past decade, deep learning has been increasingly utilized in the analysi....
Compare
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While the use of deep learning in computer vision has seen rapid growth in
unique
many different fields such as object detection, object classification, object segme....
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The impact of transfer learning on object segmentation is going to be studied in th....
unique
a) Problem definition: Development of transfer learning-based training of U-Net mod....
Keywords Words Density
1-
word
2-
words
3-
words
impact transfer learning
0.37%
retinal blood vessels
0.37%
retinal vessel segmentation
0.37%
blood vessel segmentation
0.37%
deep learning network
0.25%

12) Ethics:

Declaration of Ethics as A Computer Science Engineering Student, I believe it is Unethical To,

1. Surf the internet for personal interest and non-class related purposes during classes
2. Make a copy of software for personal or commercial use
3. Make a copy of software for a friend
4. Loan CDs of software to friends
5. Download pirated software from the internet
6. Distribute pirated software from the internet
7. Buy software with a single user license and then install it on multiple Computer
8. Share a pirated copy of software
9. Install a pirated copy of software

13) References:

List of references in the format used at the time of synopsis.

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