D.K.T.E. Society's Textile and Engineering Institute, Ichalkaranji.

(An Autonomous Institute, Affiliated to Shivaji University, Kolhapur)

Department of Computer Science & Engineering

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DKTE

Promoting Excellence in Teaching, Learning & Research

Project Report On

Segmentation of retinal fundus images using U-net model

Under the Guidance Of

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CERTIFICATE

This is to certify that,

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Have successfully completed the project work, entitled,

Segmentation of retinal fundus images using U-net model

In partial fulfilment for the award of degree of Bachelor of Technology in Computer Science and Engineering. This is the record of their work carried out during academic year 2021-2022.

Date: Place: Ichalkaranji

Prof. U. A. Nuli Prof. Dr.
D.V.Kodavade

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Thank you,

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1. INTRODUCTION

One of the most powerful ideas in deep learning is that sometimes you can take knowledge that neural network has learned from one task and apply that knowledge to other task if both tasks are related. In this project we are going to segment blood vessels from retinal fundus images using transfer learning to increase the accuracy and get good results.

In this project we are going to use Image Segmentation to segment blood vessels. Suppose we want to know where an object is located in the image and the shape of that object. We have to assign a label to every pixel in the image, such that pixels with the same label belongs to that object. Unlike object detection models, image segmentation models can provide the exact outline of the object within an image.

Differences between Image Classification, Object Detection and Image Segmentation

1.1 Related Work

Jason Yosinski et al., 2014[1]. 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 target task, which was expected, and (2) optimization difficulties related to splitting networks between co-adapted neurons, which was not expected. Paper also document 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 surprising 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., 2020[3]. 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. We observe that convolutional filters of an FCN change little during training for medical image segmentation, and still look random at convergence. We 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.

Maithra Raghu et al., 2019[7]. It explore properties of transfer learning for medical imaging. A performance evaluation on two large scale medical imaging tasks shows that surprisingly, transfer oers little benet to performance, and simple, lightweight models can perform comparably to ImageNet architectures. Investigating the learned representations and features, we nd that some of the differences from transfer learning are due to the over-parametrization of standard models rather than sophisticated feature reuse

1.2 Goals and Objectives

Goals:

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

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Objectives:

Following are the objectives of proposed system:

- To select appropriate source image domain and segmentation models
- To transfer the source model weights selectively, layer by layer to target U-Net model.
- To fine tune model training the model with small subset of target real images (Retinal images from DRIVE dataset).
- To resent 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)

1.2 Scope

- Initially we are trying to segment blood vessels from retinal fundus images. If we are able to segment blood vessel with high accuracy then we can generalize this method for other medical domains.
- So we can use this project where experts are limited persons and available dataset is also limited.

Input: Retinal Fundus Images of size 512x512 pixels.
Output: Segmented blood vessels from retinal fundus image.

2. Usage Scenario

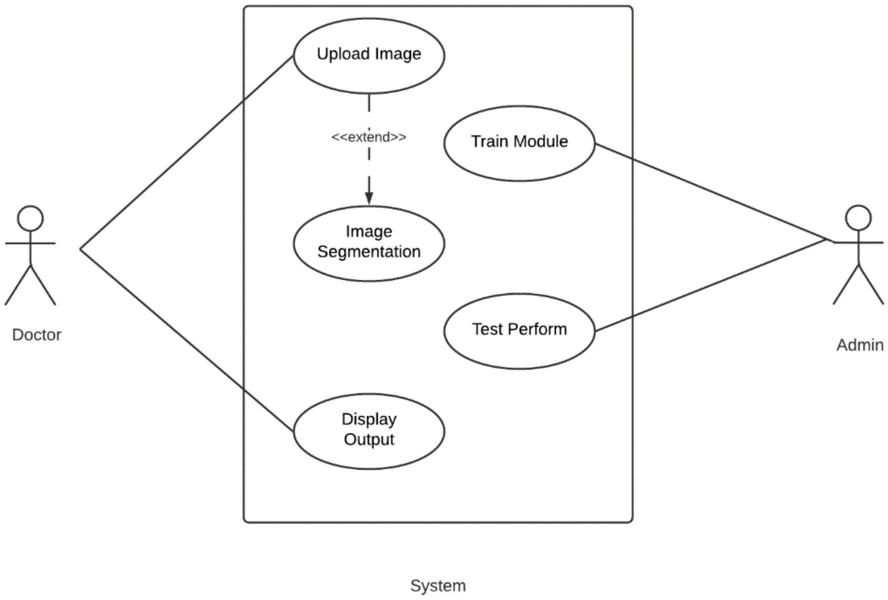
2.1 User Profiles

- Doctor
- Admin

2.2 Use Cases

- Doctor –
  Feed input image to model
  Display segmented image from model
- Admin –
  Load Test data
  Train the model
  Test the Performance

2.3 Use Cases Diagram

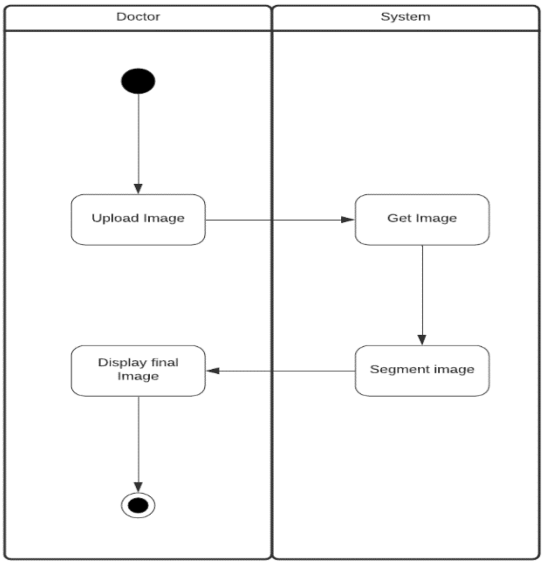


2.4 Use case Description:

Actors	Use Case	Description
Doctor	Upload Image	Get input image of size 512x512
	Image segmentation	Segment blood vessels from retinal fundus image
	Display Output	Segmented image
Admin	Train Module	Train model on real images
	Test Performance	Measure accuracy, specificity, etc.

	Load Test Data	Load test dataset for training the model.

2.5 Activity Diagram:



3. Dataset Description

- The photographs for the DRIVE database were obtained from a diabetic retinopathy screening program in The Netherlands.
- The **Digital Retinal Images for Vessel Extraction** (**DRIVE**) dataset is a dataset for retinal vessel segmentation.
- It consists of a total of 40 JPEG colour fundus images
- The screening population consisted of 400 diabetic subjects between 25-90 years of age

4. Functional Model and Description

4.1 Software Interface

Command-Line Interface script (Python) with capabilities to:

1. Get Input Image (Retinal Fundus Image)
2. Display Segmented Blood Vessels image.

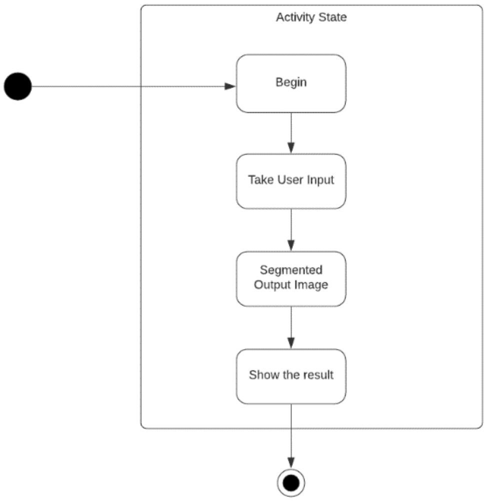
5. Behavioural model description

5.1 Events

1. **Get Input Image Event –** Get Image of Retinal Fundus image of 512x512 pixels from the user (Doctor).

2. **Display Segmented Image Event –** Display the segmented retinal fundus image segmented using U-Net Model.

4.2 State Chart Diagram:



6. Restrictions limitation and constraints:

Constrains:

1.Image input size should be 512x512

2.Image should be coloured.

3.Image should be in jpeg format.

7. Detailed Design

7.1 Components

Modules:

1.U-net:

U-net is a **convolutional neural network architecture** that expanded with few changes in the CNN architecture. **U-Net** is an architecture for semantic segmentation. It was invented to deal with biomedical images where the target is not only to classify whether there is an infection or not but also to identify the area of infection.

We are going to use this model to segment blood vessels from given retinal fundus images with high accuracy. This model will get weights from pre-trained model. These weights will be used to initialize weights for initial layers and only last few layers will be trained on scarce annotated dataset. This will help to increase the accuracy for image segmentation.

2.Gradient Decent:

Gradient descent is **an optimization algorithm** that's used when training a machine learning model. It tweaks model parameters iteratively to minimize a given function to its local minimum. It is used to minimize the cost function.

3.Pre-trained model:

This model is trained on natural images to help in the process of transfer learning. Initialized weights from this module are transferred to target U-net model.

This model is first trained on natural images. Then these weights are used to initialize weights of initial layers of U-Net model used for segmentation.

7.2 Algorithm

1. Identify suitable source pre-trained models for Transfer learning to target U-net Model having input image resolution of 565x584.
    a. Source model should have same encoder architecture as well input image size as that of target U-Net Model.
    b. Identify appropriate source image domain suitable to carry out segmentation on target U-Net model. The source model should have been trained on the identified source image domain.
2. For each of source image domain and source segmentation model transfer the weights from the pre-trained model to the target U-Net model.
    a. Copy the source model weights to the target U-Net model.
    b. Freeze the target model layer selectively

c. Train the target U- Net Model using real annotated training data (DRIVE images).
d. Test the target model for using images from DRIVE, STARE, CHASE and HRF dataset using performance parameters such as sensitivity, specificity, F1-Score, accuracy, AUC-ROC score.
3. Get Pre-trained U-Net models for natural image segmentation task and repeat steps 2.c and 2.d
4. Summarize Results.

7. Validation Criteria

Expected final software response:

1.

Describe Expected Outcome:

- Select appropriate source image domain and segmentation models
- Transfer the source model weights selectively, layer by layer to target U-Net model.
- Fine tune model training the model with small subset of target real images (Retinal images from DRIVE dataset).
- Record performance parameters during training and testing at every stage.
- Present 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)

7. Validation Criteria

7.1 Test Plan

- We give input image, get segmented image. Then compare it with ground truth image (annotated by expert doctor). Calculate various performance metrics. If it is good then segmentation is correct otherwise it is not correct.

7. Preliminary Schedule and Budget

Tables for schedule of project and overall cost of project (hardware, s/w, power, etc.)

Hardware/Software	Cost
Computer System with i5 11th generation or above	50000
NVIDIA 1080TI GPU	10000
8GB or above RAM	5000
Python IDE to run machine Learning Modules	0

8. References

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

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