SEGMENTATION OF CARONARY ARTERY USING SEGNET ARCHITECTURE

Dissertation submitted in fulfilment of the requirements for the Degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

By

MEDA RUTHUMMA(N130417)

TAMADA SRIKANYA(N130659)

KAMATHAM VEERA VANITHA(N130661)

Under the guidence of

M.V BHANU PRAKASH

Department of Computer Science and Engineering

RajivGandhiUniversityofKnowledgeTechnologies–Nuzvid

Nuzvid, Krishna –521202

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RAJIV GANDHI UNIVERSITY OF KNOWLEDGE TECHNOLOGIES
(A.P. Government Act 18 of 2008)
RGUKT-NUZVID, Krishna Dist - 521202
Tele Fax : 08656 – 235557/235150

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CERTIFICATE OF COMPLETION

This is to certify that the work entitled, “Segmentation of Caronary Artery Using Segnet Architecture” is the bonafied work of M.Ruthumma , ID No: N130417, T.Srikanya , ID No: N130659 and K.Veera Vanitha , ID No : N130661 carried out under my guidance and supervision for final year project of Bachelor of Technology in the department of Computer Science and Engineering under RGUKT IIIT Nuzvid. This work is done during the academic session August 2018 – May 2019, under your guidance.

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Mr.M.V.Bhanu Prakash	Mr.R.Upendar Rao
Project Supervisor	Head of Department
Assistant professor in Dept. of CSE	Faculty Dept. of CSE
RGUKT IIIT Nuzvid, Nuzvid	RGUKT IIIT Nuzvid, Nuzvid

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RGUKT-NUZVID, Krishna Dist - 521202
Tele Fax : 08656 – 235557/235150

CERTIFICATE OF EXAMINATION

This is to certify that the work entitled, "Segmenation(Caronary Artery)using segnet" is the bonafide work of M.Ruthumma, ID No: N130417, T Srikanya, ID No: N130659, and K.Veera Vanitha ID No:N130661 and here by accord our approval of it as a study carried out and presented in a manner required for its acceptance in final year of Bachelor of Technology for which it has been submitted. This approval does not necessarily endorse or accept every statement made, opinion expressed or conclusion drawn, as a recorded in this thesis. It only signifies the acceptance of this thesis for the purpose for which it has been submitted.

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Mr.Bhanu Prakash **Examiner**

Project Supervisor
Assistant
Professor in
Dept.of CSE
RGUKT IIIT Nuzvid, Nuzvid

RAJIV GANDHI UNIVERSITY OF KNOWLEDGE TECHNOLOGIES
(A.P. Government Act 18 of 2008)
RGUKT-NUZVID, Krishna Dist - 521202
Tele Fax : 08656 – 235557/235150

DECLARATION

We, M.Ruthumma , ID No: N130417, T.Srikanya, ID No: N130659 and K.Veera Vanitha hereby declare that the project report entitle "Segmentation of Caronary Artery using Segnet Architecture" done by us under the guidance of Mr. Bhanu Prakash is submitted for final year of Bachelor of Technology in Computer Science and Engineering the academic session August 2018 – April 2019 at RGUKT – Nuzvid.

We also declare that this project is a result of our own effort and has not been copied or imitated from any source. Citations from any websites are mentioned in the references.

The results embodied in this project report have not been submitted to any other university or institute for the award of any degree or diploma.

Date : ___________ M, Ruthumma[N130417]

Place :________ T. Srikanya[N130659]

K.Veera Vanitha [N130661]

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At this juncture we feel deeply honored in expressing our sincere thanks to him for making the resources available at right time and providing valuable insights leading to the successful completion of our project.

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Last but not least I thank almighty, and I place a deep sense of gratitude to my family members and my friends who have been constant source of information during the preparation of this project work.

ABSTRACT

Coronary artery disease magnetic resonance imaging (MRI) plays an important role in high-risk Coronary artery disease cancer screening, assessment of Coronary artery disease cancer risk, and clinical problem-solving. Many advanced quantitative and radiomics Coronary artery disease MRI analyses require to compute imaging features over the whole-Coronary artery disease region.Whole-Coronary artery disease segmentation, i.e., separating the whole-Coronary artery disease as an organ from the other parts imaged in Coronary artery disease MRI, sounds a simple preprocessing step but actually a very challenging process for automated computational methods, due to the low image contrast between chest muscle and Coronary artery disease tissue, intensity discontinuity along chest wall line, bias field, and variations in Coronary artery disease shapes.

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LIST OF ABBREVATION

ACRONYM	ABBREVATION
IOU	INTERSECTION OVER UNION
VGG	VISUAL GEOMETRY GROUP
FCN	FULLY CONVOLUTIONAL NETWORK
RNN	RECURRENT NEURAL NETWORK
CNN	CONVOLUTIONAL NEURAL NETWORK
CRF	CONDITIONAL RANDOM FIELDS

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CHAPTER 1

INTRODUCTION

1.1 DEEP LEARNING

This perspective gave rise to the “Neural Network” terminology. The brain contains billions of neurons with tens of thousands of connections between them. Deep learning algorithms resemble the brain in many conditions, as both the brain and deep learning models involve a vast number of computation units (Neurons) that are not extraordinarily intelligent in isolation but become intelligent when they interact with each other.

1.1.1 Neurons

The basic building block for neural networks are artificial neurons, which imitate human brain neurons. These are simple, powerful computational units that have weighted input signals and produce an output signal using an activation function. These neurons are spread across the several layers in the neural network.

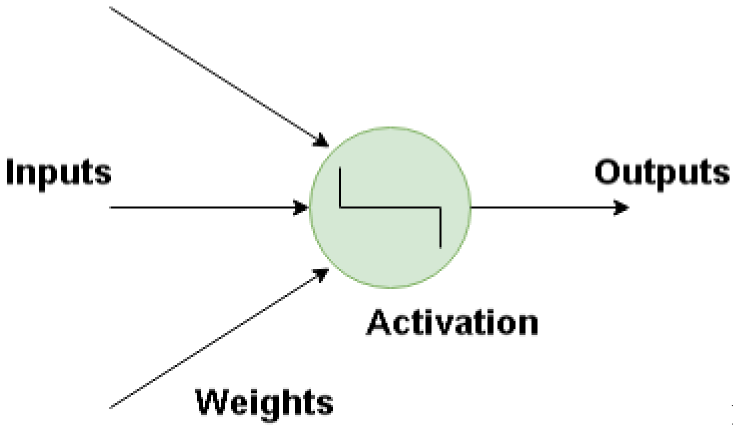


Fig 1

1.1.2 How Does Artificial Neural Network Works?

Deep learning consists of artificial neural networks that are modelled on similar networks present in the human brain. As data travels through this artificial mesh, each layer processes an aspect of the data, filters outliers, spots familiar entities, and produces the final output.

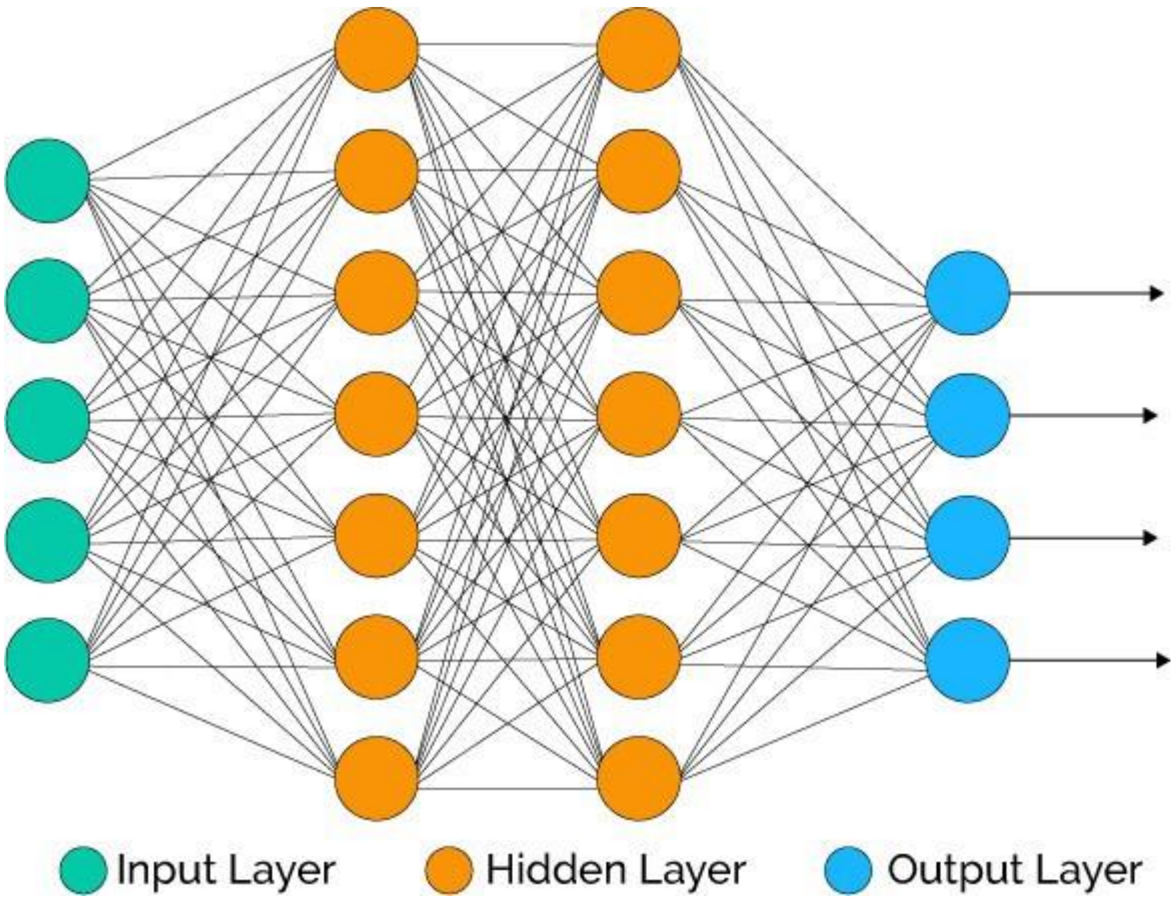


Fig 2

Input layer : This layer consists of the neurons that do nothing than receiving the inputs and pass it on to the other layers. The number of layers in the input layer should be equal to the attributes or features in the dataset.

Output Layer: The output layer is the predicted feature, it basically depends in the type of model you're building.

Hidden Layer: In between input and output layer there will be hidden layers based on the type of model. Hidden layers contain vast number of neurons. The neurons in the hidden layer apply transformations to the inputs and before passing them. As the network is trained the weights get updated, to be more predictive.

Neuron Weights

Weights refer to the strength or amplitude of a connection between two neurons, if you are familiar with linear regression you can compare weights on inputs like coefficients we use in a regression equation.Weights are often initialized to small random values, such as values in the range 0 to 1.

1.2 Feedforward Deep Networks

Feedforward supervised neural networks were among the first and most successful learning algorithms. They are also called deep networks, multi-layer Perceptron (MLP), or simply neural networks and the vanilla architecture with a single hidden layer is illustrated. Each Neuron is associated with other neuron with some weight,

The network processes the input upward **activating** neurons as it goes to finally produce an output value.This is called a forward pass on the network.

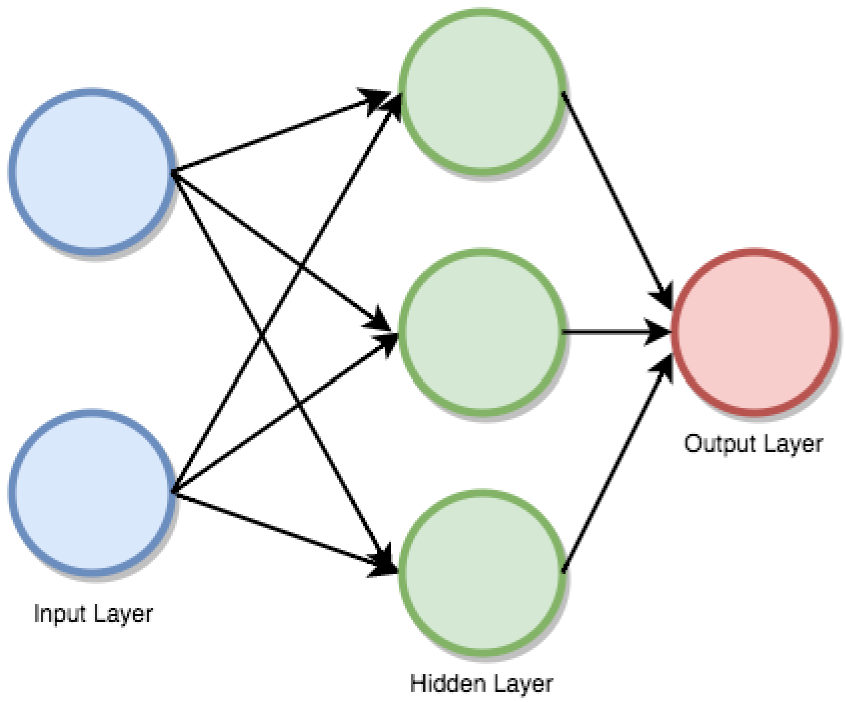


Fig 3

Activation Function

An activation function is a mapping of summed weighted input to the output of the neuron. Because it governs the inception at which the neuron is activated and the strength of the output signal.

Mathematically ,

$$Y = \Sigma(weight * input) + bias$$

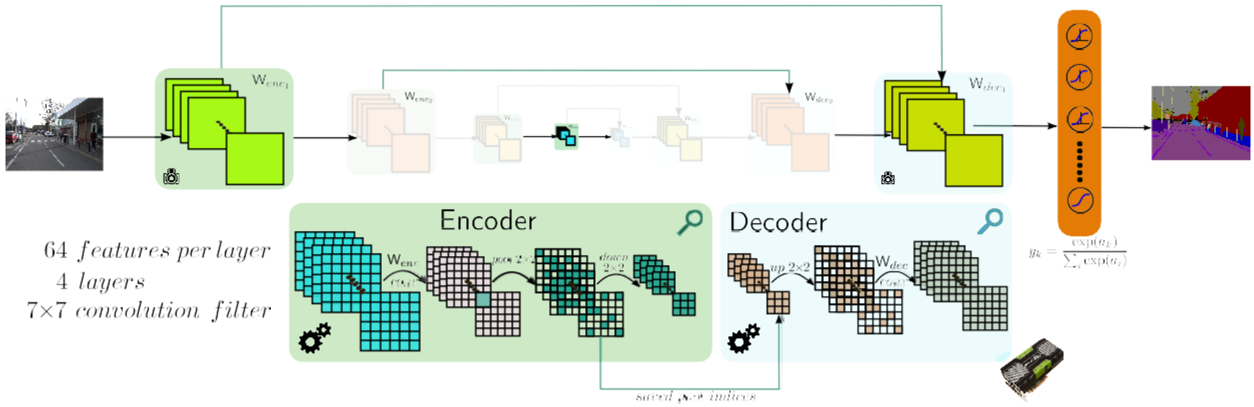


Fig 4:*pervised*manner for pixel-wise labelling

The SegNet predictions get smoother as more layers are added and demonstrate highac- curacy, comparable to or even exceeding methods which use CRFs[36].SegNet maintains a constant number of features perlayer which is typically set to 64.This has a practical ad- vantage that the computational cost successively decreases for each additional/deeper encoder-decoder pair.

1.3 LITERATURE SURVEY

Computer vision and image analysis is the most important task of image segmentation. Several proposals to divide object feature extractions have been put forward . However, research challenges in the design of efficient and robust segmentation algorithms, owing to the complexity and variety of the images, remain (Yang and Tianzi, 2009). The aim of image segmentation is the division of the image into sectors which overlap with each other and are inconsistent in relation to definite properties like density, tone, color, and defined texture homogeneity.

CHAPTER 2

EXISTING SYSTEM

The first approaches employing deep learning methods for image segmentation were similar to the ones, which already examined earlier in previous image processing and pattern recognition works. They tried to directly adopt deep learning architectures for categorization small image patches or pixel neighborhoods to certain classes . More recently, Vijay Badrinarayanan and colleagues from University of Cambridge have presented a novel and practical deep fully convolutional neural network architecture for semantic pixel-wise segmentation termed as unet. This core trainable segmentation engine consists of an encoder network, corresponding decoder network followed by a pixel-wise classification layer. The role of the decoder network is to map the low resolution encoder feature maps to full input resolution feature maps for pixel-wise classification.

CHAPTER 3

PROPOSED SYSTEM

In order to do segmentation, image blocks are taken (with an odd number of pixels – the central pixel plus neighbourhood) to determine the class (vessel or non-vessel) of the central pixel. Network training is performed on patches extracted from a set of images for which a manual segmentation exists. After such training, the network can be used to clas- sify each pixel in the new examples of images After alternating four steps of C and MP layers two FC layers further combine the outputs into a 1D feature vector. The last layer is always a FC layer with one neuron per class (two in our case due to binary classification). In the output layer by using Softmax activation function each neuron’s output activation can be taken as the probability of a particular pixel.

CHAPTER 4

SYSTEM IMPLEMENTATION

System implementation covers a broad spectrum of activities from a detailed workflow analysis to the formal go-live of the new system. During system implementation organizations may refine the initial workflow analysis that had been completed as part of the requirements analysis phase. With the aid of the vendor they may also start mapping out the proposed new workflow.

The system implementation phase requires the vendor to play a very prominent role. In addition to the workflow analysis it is during this phase that full system testing is completed. Other key activities that would occur during this phase include piloting of the new system, formal go-live and the immediate post implementation period during which any application issues are resolved.

4.1 Implementation Process

The implementation process begins with preparing a plan for the implementation system. According to this plan, the other activities are to be carried out. In this plan, discussion has been made regarding the equipment, resources and how to test the activities.

Post Implementation Review

The Post Implementation Review (PIR) process collects and utilizes knowledge learned throughout a project to optimize the delivery and outputs of future projects. A PIR can be used on projects ranging from the design and construction of buildings to the development of an asset strategy or an asset register. PIR is a process, a tool and a means of collecting and communicating information. A PIR can

4.2 Methods

We designed a fully automated deep learning-based segmentation algorithm using the SegNet model. “SegNet” consists of a stack of convolutional layers (encoder network) with their corresponding de-convolutional layers (decoder network), followed by a final pixel-wise classification layer. The encoder network consists of 13 convolutional layers and each encoder layer has a corresponding decoder layer. To produce class probabilities for each pixel independently, the final decoder output is connected to a multi-class soft-max classifiers. The SegNet model will be implemented using the Caffe platform running on a desktop computer system with the following specifications: Intel® Core™ i7-4790 CPU@3.60GHZ with 8 GB RAM and a Titan X Pascal Graphics Processing Unit (GPU). In addition to using the GPU to accelerate training, we also used rectified linear units (ReLU) in place of the traditional tangent function and the sigmoid function as the activation function to further speed up the training.

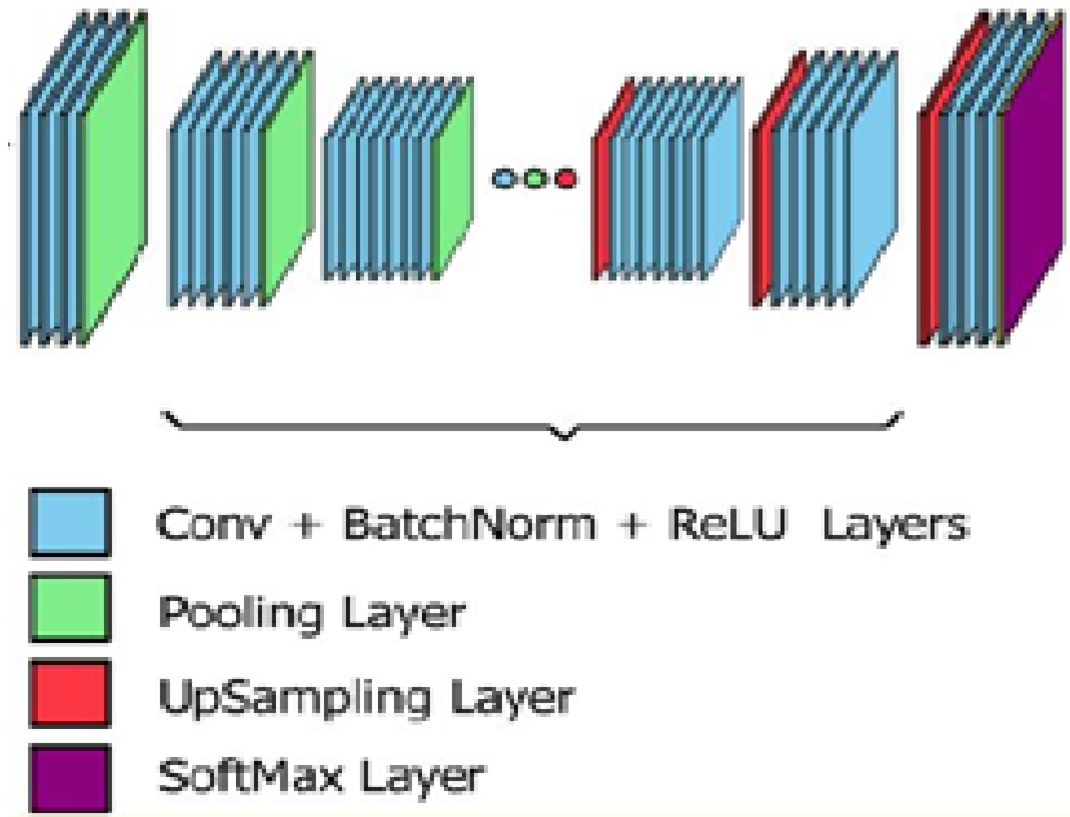


Fig:5

The basic elements of the SegNet neural network architecture (Fig. 2) can be viewed as a stack of convolution layers (Encoder) with their corresponding de-convolution layers (Decoder). The network architecture used in this work had 4 encoding and 4 decoding layers. Every encoder layer reduces the input feature map size by factor of 2. Therefore, the combined sub-sampling rate was equal to 16. It is commonly known that large scaling factors can potentially improve desired properties of displacement, rotation and scale invariance of the convolution network being considered in the spatial domain. Also, in case of chest X-Ray image segmentation, the original input images already partly aligned due to the natural top-bottom orientation of

In this work we used ReLU as the nonlinear activation function [13]. The

MaxPooling sub-sampling was used on the encoding stage and MaxPooling up-sampling (un- pooling) utilized for the decoding stage. At every stage, the window size was set to a small patch of 2x2 pixels in size, without overlapping.

It is known that the problem of unpooling in decoder layers is not uniquely defined. In order to solve this problem in SegNet, the upsampling of feature map in decoder layer was implemented using max-pool index from corresponding encoder layer (see Fig. 3). Every convolution and deconvolution layer maintains a fixed number of filters (Fig. 3), which was set to 64 filters.

On the final layer of ED-CNN neural network we used SoftMax function of the following type:

$$y_k = \frac{\exp(x_k)}{\sum_i \exp(x_i)}$$

At the classification stage, the following two techniques have been used for reducing the influence of X-Ray intensity variations in the original images to the neural network being employed:

(a) At a preprocessing stage, we transform the intensity of each input image using the histogram equalization technique [14].

(b) The Local Contrast Normalization (LCN) procedure [15] was applied at the input of encoding layers.

CHAPTER 5
SYSTEM DESIGN

5.1 SYSTEM DESIGN

The system design phase converts the general requirements defined in the analysis phase into detailed specification for the new system. Until now, the analyst has been using the general knowledge about the specific operations, and an ability to get information from the people.

Based on the user requirements, the new system must be designed. This is the system design phase, which is the most crucial phase in the development of the system.

Developing a real time application for any system utilities involves two processes namely,

- The first process is to design the system and implement it.
- The second process is to construct the executable code.

Design refers to the process of translating performance specifications recommended in analysis phase into design specifications.

The process of design involves –

- Input Design
- Output Design
- Database Design

Input design:

Input design is the process of converting user-oriented formats to computer-based formats. The input design in made user-friendly, in such a way that they could enter data online through a keyboard. A formatted form is a preprinted form that requests the user to enter data in appropriate locations.

Output Design:

The normal procedure in developing a system is to design the output in detail first and then move back to the input. The output will be in the form of views and reports. The output from the system is required to communicate the result of processing to the users. They are also used as the permanent copy for later verifications.

System Model

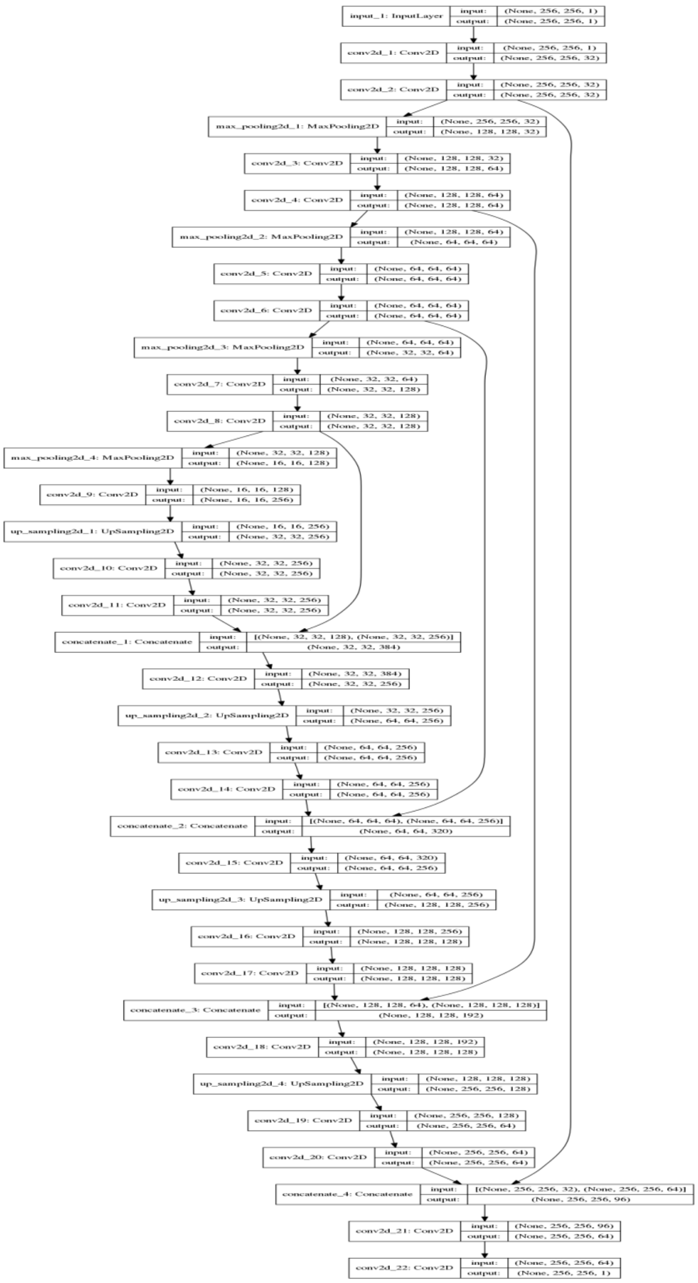


Fig 6

5.2 DESCRIPTION OF A SYSTEM

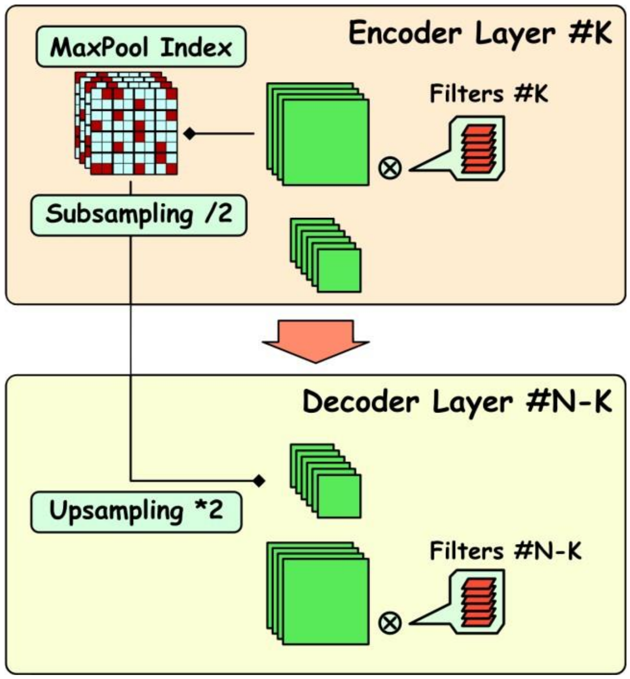


Fig 7

5.3 SEGNET ARCHITECTURE

A four layer SegNet architecture used in our experiments is illustrated below. Each encoder performs dense convolutions, ReLU non-linearity, a non-overlapping max pooling with a 2*2 window and finally down-sampling. Each decoder up samples its input using the memorized pooledin- dices and convolves it with a trainable filterbank .NoReLU non linearity is used in the decoder unlike the deconvolution network [41, 42]. This makes it easier to optimize the filters in each pair. The encoder and decoder filters are also untied to provide additional degrees of freedom to minimize the objective. The final layer is a soft-max classifier (with nobiasterm)whichclassifieseachpixelindependently.The output of the soft-max is a K channel image where K is the number ofclasses.

SegNet uses a “flat” architecture, *i.e*, the number of features in each layer remains the same (64 in our case) but with full connectivity. This choice is motivated by two reasons. First, it avoids parameter explosion, unlike an expanding deep encoder network with full feature connectivity (same for decoder). Second, the training time remains the same (in our experiments it slightly decreases) for each additional/deeper encoder-decoder pair as the feature map resolutionissmallerwhichmakesconvolutionsfaster.Note that the decoder corresponding to the first encoder (closest to the input image) produces a multi-channel feature map although the encoder input is either 3 or 4 channels (RGB or RGBD) (see Fig. 1). This high dimensional feature rep- resentation is fed to the soft-max classifier. This is unlike the other decoders which produce feature maps the same sizeastheirencoderinputs. Afixedpoolingwindowof

22 with a stride of non-overlapping×2 pixels is used. This small size preserves thin structures in the scene. Further, a constant × kernel size of 7 7 over all the layers was cho- sen to provide a wide context for × smooth labelling*i.e.* a pixel in the deepest layer feature map can be traced back to a context window in the input image of 106 106 pixels. The trade-off here is between the size of the context win- dow and retaining thin structures. Smaller kernels decrease context and larger ones potentially destroy thinstructures. The input to the SegNet can be any arbitrary multi- channel image or feature map(s), *e.g.*, RGB,

RGBD, map of normals, depth etc. We perform local contrast normalization(LCN)asapre-processingsteptotheinput[23,15]. The advantage of this step are many, (i) to correct for non-uniform scene illumination thus reducing the dynamic range (increases contrast in shadowed parts). (ii) highlight- ing edges which leads the network to learn categoryshape,

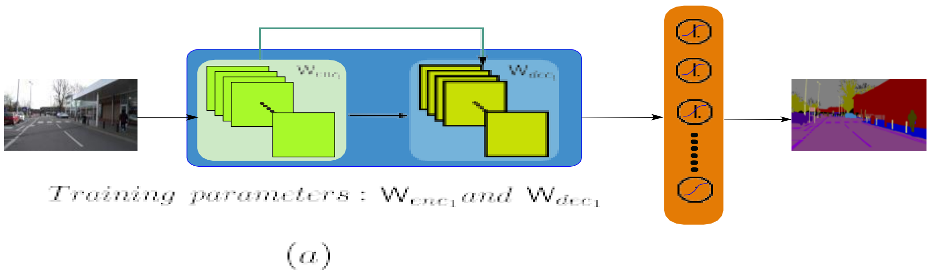


Fig 8

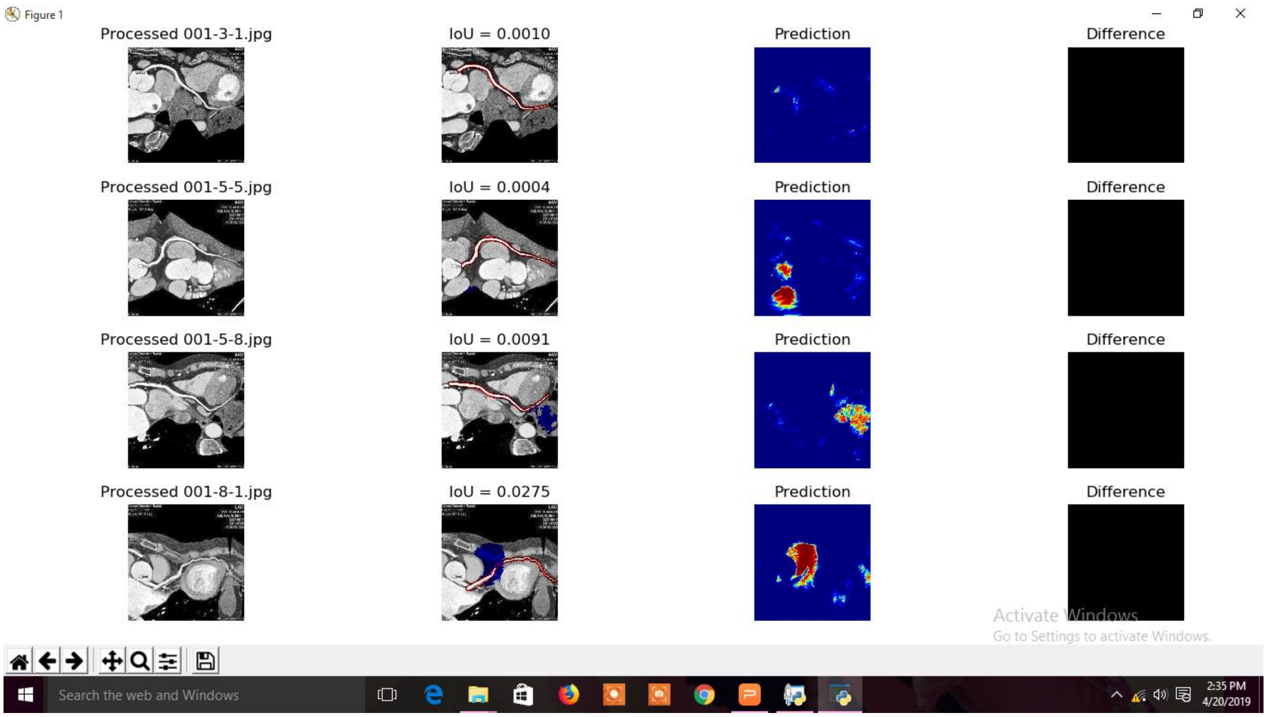


Figure 1
Processed 001-3-1.jpg
IoU = 0.0010
Prediction
Difference
Processed 001-5-5.jpg
IoU = 0.0004
Prediction
Difference
Processed 001-5-8.jpg
IoU = 0.0091
Prediction
Difference
Processed 001-8-1.jpg
IoU = 0.0275
Prediction
Difference
Activate Windows
Go to Settings to activate Windows.
Search the web and Windows
2:35 PM
4/20/2019

Fig 9

CHAPTER 6

SYSTEM TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

6.1 TYPES OF TESTS

6.1 1 Unit testing

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application, and/or system configuration.

6.1.2 Integration testing

Integration tests are designed to test integrated software components to determine if they actually run as one program. Testing is event driven and is more concerned with the basic outcome of screens or fields. Integration tests demonstrate that although the components were individually satisfaction, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components

Functional test

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input : identified classes of valid input must be accepted.

Invalid Input : identified classes of invalid input must be rejected.

Functions : identified functions must be exercised.

Output : identified classes of application outputs must be exercised.

Systems/Procedures : interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases. In addition, systematic coverage pertaining to identify Business process flows; data fields, predefined processes, and successive processes must be considered for testing. Before functional testing is complete, additional tests are identified and the effective value of current tests is determined.

System Test

System testing ensures that the entire integrated software system meets requirements. It tests a configuration to ensure known and predictable results. An example of system testing is the configuration oriented system integration test. System testing is based on process descriptions and flows, emphasizing pre-driven process links and integration points.

6.1.3 White Box Testing

White Box Testing is a testing in which in which the software tester has knowledge of the inner workings, structure and language of the software, or at least its purpose. It is purpose. It is used to test areas that cannot be reached from a black box level.

6.1.4 Black Box Testing

Black Box Testing is testing the software without any knowledge of the inner workings, structure or language of the module being tested. Black box tests, as most other kinds of tests, must be written from a definitive source document, such as specification or requirements document, such as specification or requirements document. It is a testing in which the software under test is treated, as a black box .you cannot "see" into it.

Test objectives

- All field entries must work properly.
- Pages must be activated from the identified link.
- The entry screen, messages and responses must not be delayed.

- Verify that the entries are of the correct format.
- No duplicate entries should be allowed.

6.1.5 Acceptance Testing

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

Test Results: All the test cases mentioned above passed successfully. No defects encountered.

CHAPTER 7

RESULTS

Fig 10. Testing accuracyTensorboard graph

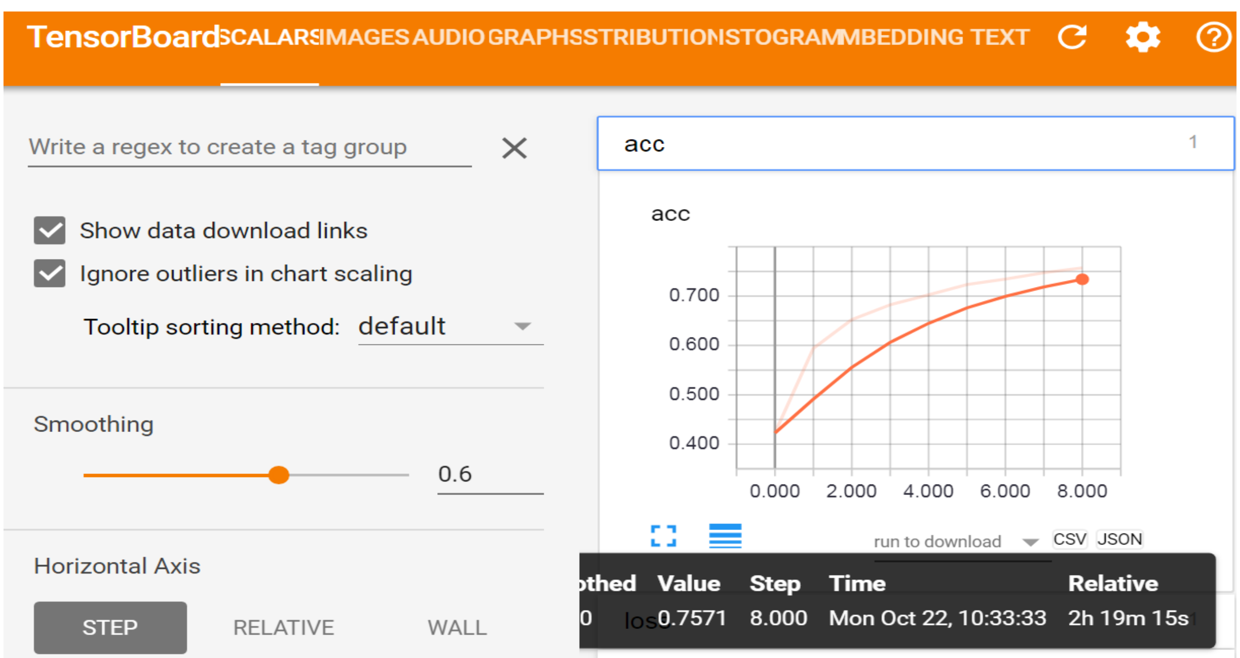


Fig 11. Testing loss tensorboard graph

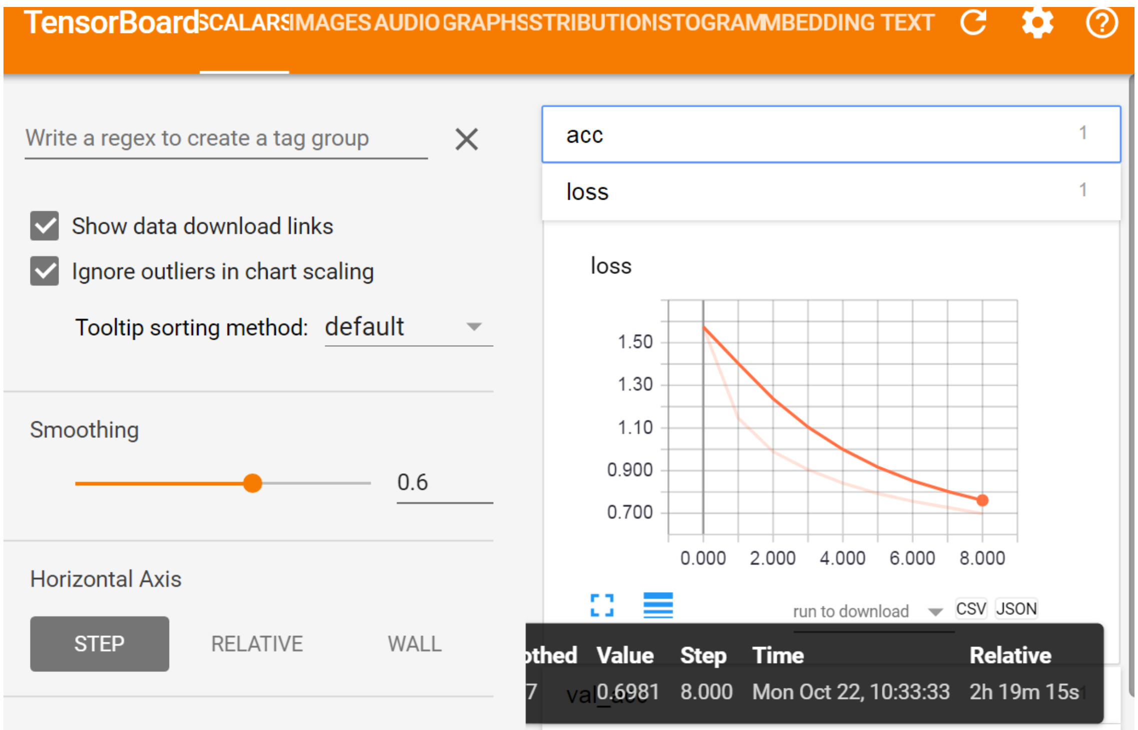


Fig 12. Test Validation accuracy

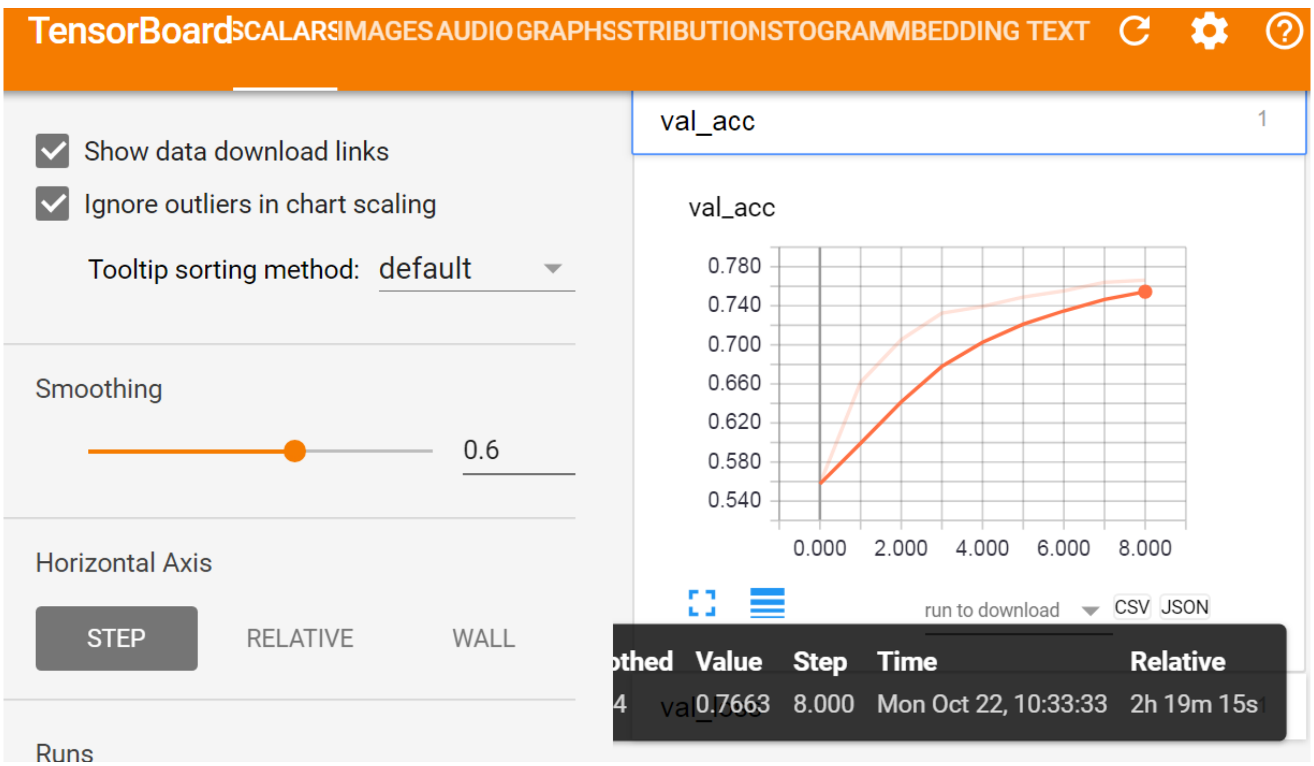


Fig 13. test validation loss

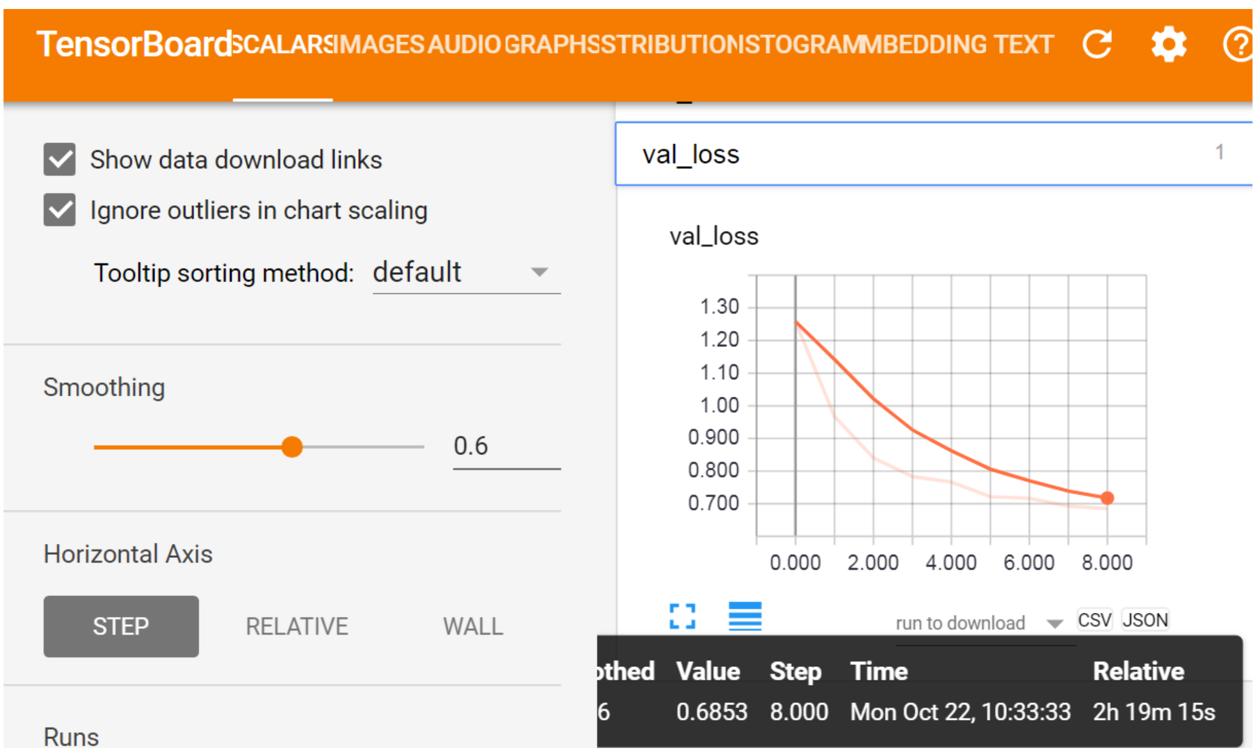


Fig 14. training validation accuracy

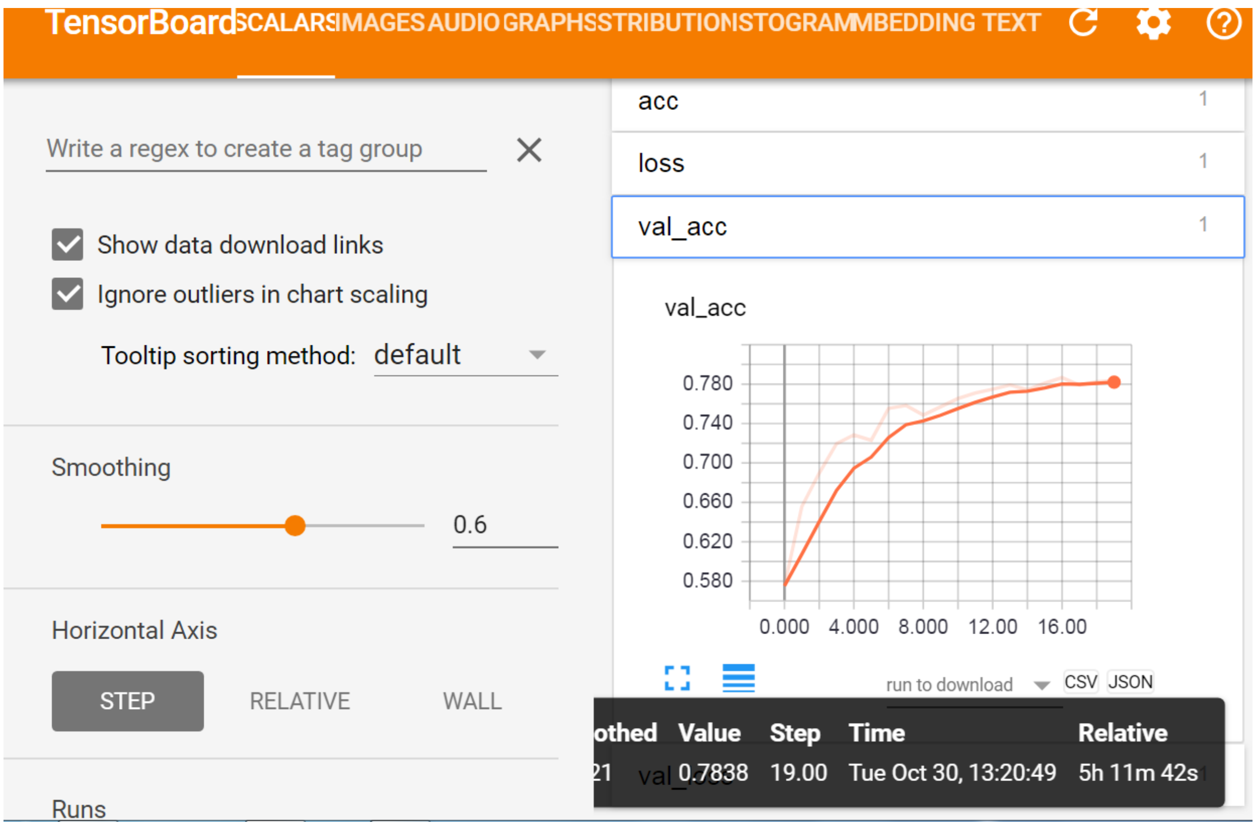
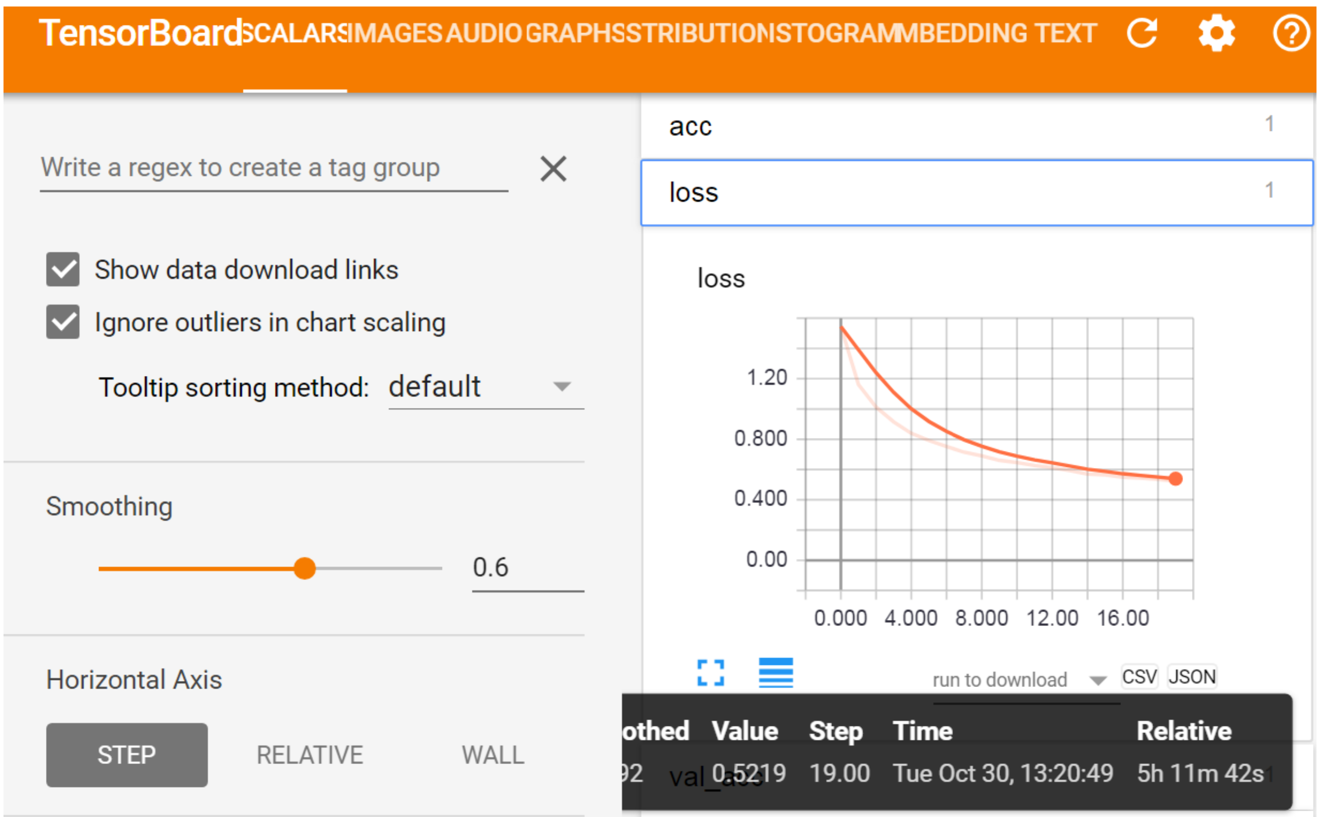


Fig 15. Traning validation loss



OVERALL PERFORMANCE RESULT

Table 1

	ACCURACY	**LOSS**
TRAINING	0.8170	0.5219
TESTING	0.7663	0.6853
VALIDATION	0.7838	0.6389

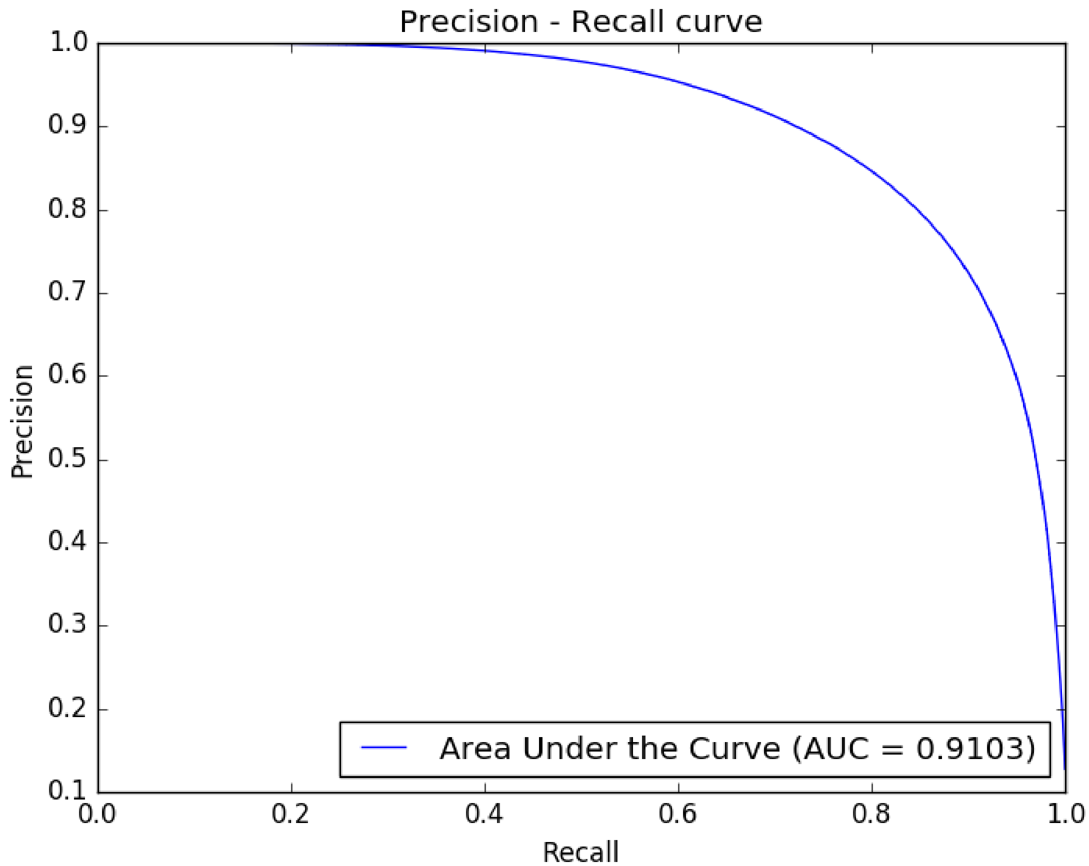

Precision - Recall curve
Precision
Recall
Area Under the Curve (AUC = 0.9103)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.2
0.4
0.6
0.8
1.0

Fig16

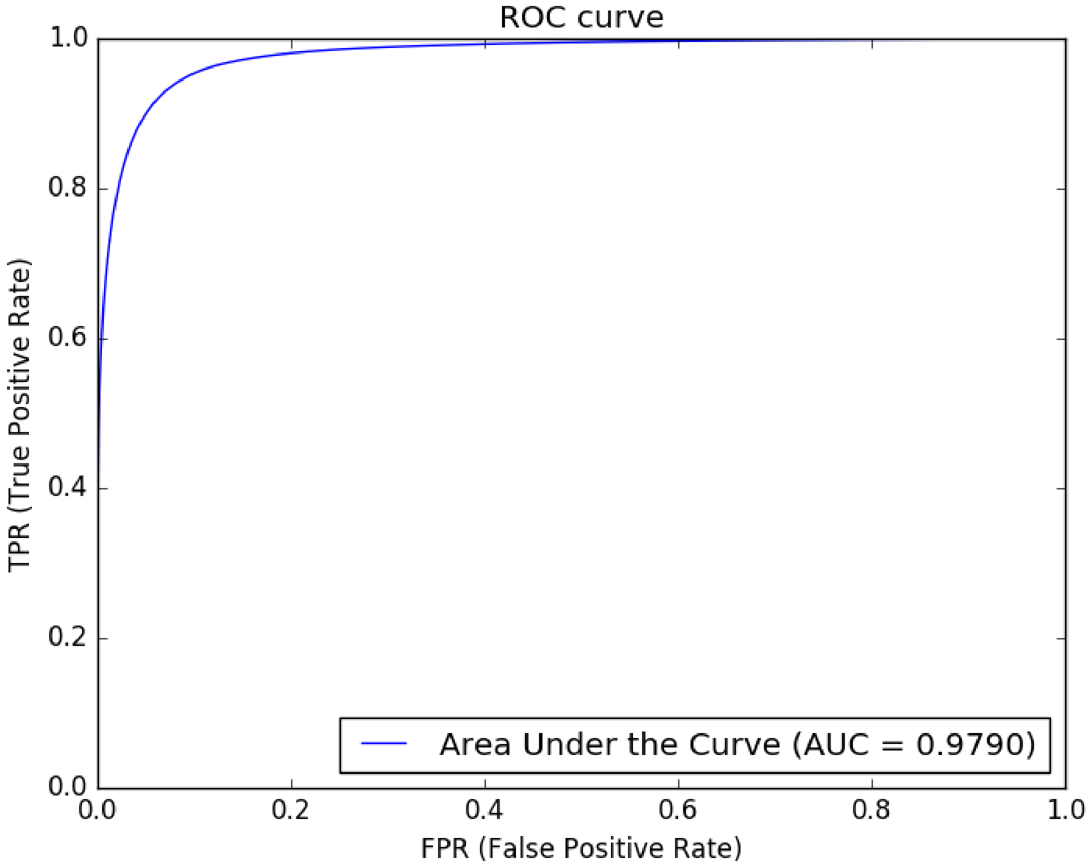

ROC curve
1.0
0.8
0.6
0.4
0.2
0.0
TPR (True Positive Rate)
0.0
0.2
0.4
0.6
0.8
1.0
FPR (False Positive Rate)
Area Under the Curve (AUC = 0.9790)

Fig17

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

8.1 CONCLUSION

We presented SegNet, a deep convolutional network architecture for semantic segmentation.

The main motivation behind SegNet was the need to design an efficient architecture for bio-medical images understanding which is efficient both in terms of memory and computational time.

8.2 FUTURE SCOPE

Since now a days more and more hybrid archtires are used for implementation for segmentation in deep neural networks we can implement the in future the hybrid archtire using segnet which can extended the accuracy above 95% which can give better results in finding the dieases.

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